Analytical Research of Segmentation Methods on Skin Lesion

Felsia Thompson¹ and M.K. Jeyakumar²

¹Research Scholar, Department of Computer Applications, Noorul Islam University, Kumaracoil, Tamil Nadu, India.
²Professor, Department of Computer Applications, Noorul Islam University, Kumaracoil, Tamil Nadu, India.

Abstract
Melanoma or Skin lesion is the most dangerous type of skin cancer. If melanoma is recognized and treated early, it is almost always curable. In this regard, several imaging techniques have been explored to improve the diagnosis accuracy of skin lesions. The first step in these systems is skin lesion segmentation. The next essential step is feature extraction and pattern analysis procedures for better recognition. Various existing segmentation methods adopted by different authors have been presented such as Adaptive thresholding. Thresholding based on type-2 fuzzy logic, statistical region merging, Neuro fuzzy model, Geometric deformable models, Levelset model, Wavelet network model and fuzzy c-means clustering model. The segmentation methods discussed here are thresholding, edge-based, region-based and cluster based. Color images when segmented directly, yields better differentiation between the lesions. These techniques are evaluated using Accuracy rate, sensitivity, specificity, Border error, Hammoude distance, MSE, PSNR and elapsed time.

Keywords: image segmentation, melanoma, neuro fuzzy, region merging, thresholding, wavelet network

INTRODUCTION
Skin cancer is the most common type of cancer in the United States. There are three main types of skin cancer: basal-cell cancer (BCC), squamous-cell cancer (SCC) and melanoma [2]. The first two together along with a number of less common skin cancers are known as non-melanoma skin cancer (NMSC). Non-melanoma skin cancer is usually curable but Melanomas are the most aggressive. Malignant melanoma on its own can sometimes is referred to as ‘skin cancer’ [19]. Malignant melanoma accounts for 75 percent of all deaths associated with skin cancer in United States [22]. It can originate in any part of the body that contains melanocytes. Nevertheless, it can be treatable, if diagnosed at an early stage[1].

Dermoscopy is a non-invasive diagnosis technique for the in vivo observation of pigmented skin lesions used in dermatology [3]. Dermoscopic images have great potential in the early diagnosis of malignant melanoma, but their interpretation is time consuming and subjective, even for trained dermatologist’s. Therefore, there is currently a great interest in the development of computer-aided diagnosis systems that can assist the clinical evaluation of dermatologists. The standard approach in automatic dermoscopic image analysis has usually three stages: 1) image segmentation; 2) feature extraction and feature selection; and 3) lesion classification.

Segmentation is the most important part in image processing. It is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. However, segmentation is difficult because of the variation of lesion shapes, sizes, and colors and also with different skin types and textures. In automated diagnosis of skin lesions, feature design is based on the ABCD rule of dermatoscopy. ABCD represent the asymmetry, border structure, variegated color, and dermatscopic structures and define the basis for a diagnosis by dermatologist [20].

To address the segmentation problem, several algorithms have been proposed. They can be broadly classified as thresholding, edge based, region-based and clustering based methods. Thresholding is the easiest way of segmentation. It is done through that threshold values which are obtained from the histogram of those edges of the original image. These methods can achieve good results when there is good contrast between the lesion and the skin. In the edge based segmentation techniques, edges are detected to identify the discontinuities in the image. Edges on the region are traced by identifying the pixel value and it is compared with the neighboring pixels. Edge-based approaches used in [4] where the segmentation is based on the zero-crossings of the Laplacian-of-Gaussian and in several active contour methods like the gradient vector flow (GVF) used in [21]. Edge-based approaches perform poorly when the boundaries are not well defined, for instance when the transition between skin and lesion is smooth.

In region based methods, especially in Statistical Region Merging, regions are sets of pixels with homogeneous properties and they are iteratively grown by combining smaller regions [9], [10]. This merging algorithm works with a statistical test which is based on a merging predicate and an order of merging. In deformable model, the segmentation is treated as a curve evolution and the final status of the moving contour(s) is defined as the object boundary [12]. Artificial intelligence field, especially using fuzzy and artificial neural network (NN) approaches for segmentation of medical images, has gain special popularity [17]. One of the most promising computational intelligence methods that have been widely used for various applications in different areas is wavelet network (WN)[16].

In Clustering-based methods, the gray-level samples are clustered in two parts as background and foreground (object),
or alternately are modeled as a mixture of two Gaussians. A basic clustering algorithm i.e., K-means is used for segmentation in textured images. This algorithm divides an image into K segments, minimizing the total within-segment variance. For segmentation of color image they use Fuzzy Clustering technique, which iteratively generates color clusters using Fuzzy membership function in color space regarding to image space.

This paper discusses and evaluates several segmentation methods of the four classes: thresholding, edge-based, region-based and clustering based. Evaluation is by specificity, sensitivity, accuracy, border error, Hammoude distance, MSE, PSNR and elapsed time values.

The organization of this paper is as follows: Several Segmentation techniques are summarized in Section II. In Section III, evaluation results are presented. Section IV discusses the results and Section V concludes the result.

SEGMENTATION TECHNIQUES

Image segmentation is an essential step in image analysis and image representation tasks. Image segmentation algorithms are categorized under thresholding, region-based, edge based and clustering based, techniques. This paper discusses and compares the following segmentation methods.

- Adaptive thresholding
- Thresholding based on type-2 fuzzy logic
- Statistical region merging
- Neuro fuzzy model
- Geometric deformable models
- Levelset model
- Wavelet network model
- Fuzzy C-Means Clustering Algorithm

Adaptive Thresholding

Lesion is segmented by average threshold and standard deviation over the histogram area [6]. Locate the threshold range R contains series of k threshold intervals. R value changes image to image. For ith threshold interval, i=1, …, k is given by

\[ i = \left\{ M - \frac{1}{2} R + \frac{i - 1}{k} R, M - \frac{1}{2} R + \frac{i}{k} R \right\} \]

Pixels within the R of the following four classes

1. Pixels within R = True Positive (TP)
2. Pixels missed within R = False Negative (FN)
3. Pixels outside R = False Positive (FP)
4. Pixels missed outside R = True Negative (TN)

A Simple signal to noise ratio is calculated from the parameters TP and FP as, TP/FP. The output generated is in the form of binary image. The possible errors occur are, within R = FN/(FN + TP) outside R = FP /(FP + TN)

The new error measure adds the said possible errors. The main difficulty in this method is the setting up of upper and lower bound of R.

Thresholding based on type-2 fuzzy logic

This method used in this study is a fuzzy-based thresholding technique, recently discussed by M. Emin Yuksel [7] and J. Maeda [8]. The algorithm originally aims at finding the threshold based on type-2 fuzzy set. It is characterized by the membership function \( \mu_A(x, u) \), where \( x \in \mathbb{R} \), \( u \in [0, 1] \)

\[ A = \{(x, u) \mid \forall x \in \mathbb{R}, u \in [0, 1] \} \]

(4)

or

\[ A = \bigcap_{x \in \mathbb{R}} \mu_A(x, u) / \{(x, u) \} \]

(5)

where \( \bigcap \) denotes overall union admissible x and u.

Mathematically

\[ A = \{(x, u) \mid \forall x \in \mathbb{R}, u \in [0, 1] \} \]

(6)

or

\[ A = \bigcap_{x \in \mathbb{R}} 1 / \{(x, u) \}, J_1 \subseteq \{0, 1\} \]

(7)

Generally, the fuzziness of a fuzzy set is related with its membership function. If the membership function is steep, then the fuzzy set is said to be rather crisp. If the membership function is flat, it is highly fuzzy. The term ultra fuzziness refers to degree of fuzziness of type-2 fuzzy set.

Ultra fuzziness is defined as follows,

\[ F(A) = \frac{1}{MN} \sum_{g=0}^{L-1} h(g) [\mu U(g) - \mu L(g)] \]

(8)

where \( A (A \subseteq X) \) is the subset of the given image, \( M \times N \) is the size of the subset, \( L \) is the number of possible gray levels, g is the color value \( g \in [0, L - 1] \), and \( h(g) \) is the histogram of the image.

Statistical region merging

The Statistical Region Merging discussed by Nock and Neilson [9] and Celebi M [10] is a region merging segmentation technique. The idea is to start with one region per pixel and then applying a statistical test on neighboring regions (in ascending order of intensity differences) whether the mean intensities are sufficiently similar enough to be merged. The image i contains RGB values, each of three belongs to the set \{1, …, g\}. In I, the optimal (or true, or statistical) regions represent theoretical objects sharing a common homogeneity property:

- Inside any statistical region and given any color channel \( \{R, G, B\} \), the statistical pixels have the same expectation for this color channel.
- The expectations of adjacent statistical regions are different for at least one color channel \( \{R, G, B\} \).

Nielsen and Nock consider a sort function \( f \) defined as follows:

\[ f(P, P') = \max |P_a - P_b| \]

(9)
Initially the initial curve is located in the lesion region, since uncertainty is more in the affected part. Then the curve move towards the lesion till the lesion boundary reaches. The level set function \( \varphi(x, y, 0) \) as follows.

\[
\varphi(x, y, 0) = \begin{cases} d(x, y) & \text{if the pixel is inside } C \\ -d(x, y) & \text{otherwise} \end{cases}
\]

(12)

Where \( d(x, y) \) is the Euclidean distance of the pixels \((x, y)\) from the initial contour \( C \).

The speed function used here is,

\[
F(x, y) = P_L(x, y) P_R(x, y) 1+k
\]

(13)

Where \( k = V \left( \frac{\varphi}{|\varphi|} \right) \) is the curvature of the curve, and

\[
F(P_L(x, y)) = \frac{1}{\sqrt{2\pi \sigma_1}} \exp \left( -\frac{(L(x, y) - \mu_1)^2}{2\sigma_1^2} \right)
\]

\[
F(P_R(x, y)) = \frac{1}{\sqrt{2\pi \sigma_2}} \exp \left( -\frac{(S(x, y) - \mu_2)^2}{2\sigma_2^2} \right)
\]

(14)

From the above all discussion, the merging predicate will be

\[
P(R, R') = \begin{cases} \text{true} & \text{if} \left| R - R' \right| \leq b(R - R') \leq b(R' - R) \left( b(R - R') \geq b(R' - R) \right) \text{ a merging} \\
\text{false} & \text{otherwise} \end{cases}
\]

(10)

Any regions \((R, R')\) from the image \( I \) and whose merging is tested should satisfy \(|R - R'| \leq b(R - R')\). Since \( b(R, R') \leq \sqrt{b^2(R) + b^2(R')} \) and the merging predicate authorize the merging of \( A \) and \( \bar{A} \). Here, \( Ra \) denotes the observed average for color channel \( a \) in region \( R \).

**Neuro Fuzzy Model**

Neuro Fuzzy based segmentation is proposed by Binamrata Baral[11], which uses decision making and neuro fuzzy based techniques. In this technique the acquired color image is converted into device independent \( L^a*b^a \) color space. \( L^a*b^a \) consist of 3 components: Brightness or luminosity, color \( a \) and color \( b \). Features like intensity also centroids of the lesion arise is that centroid of both are unknown. So the internal region of the curve is calculated by,

\[
\Omega_0^i = \{ (x, y) | -50 < \varphi(x, y, t) < 0 \}, \quad \Omega_1^i = \{ (x, y) | \varphi(x, y, t) > 0 \}
\]

(15)

The centroids of the normal skin \((a_0^*, b_0^*)\) and \((u_0^*, v_0^*)\) and also centroids of the lesion \((a_1^*, b_1^*)\) and \((u_1^*, v_1^*)\) are calculated as,

\[
a_0^* = \frac{1}{|\eta_0^a||\eta_0^b|} \sum_{\rho \in \eta_0^a} a_p^* b_p^* = \frac{1}{|\eta_0^a||\eta_0^b|} \sum_{\rho \in \eta_0^a} a_p^* b_p^*
\]

\[
\eta_0^a = \frac{1}{|\eta_0^a||\eta_0^b|} \sum_{\rho \in \eta_0^a} a_p^* b_p^*
\]

\[
u_0^* = \frac{1}{|\eta_0^a||\eta_0^b|} \sum_{\rho \in \eta_0^a} u_p^* v_p^* = \frac{1}{|\eta_0^a||\eta_0^b|} \sum_{\rho \in \eta_0^a} u_p^* v_p^*
\]

\[
u_1^* = \frac{1}{|\eta_1^a||\eta_1^b|} \sum_{\rho \in \eta_1^a} u_p^* v_p^* = \frac{1}{|\eta_1^a||\eta_1^b|} \sum_{\rho \in \eta_1^a} u_p^* v_p^*
\]

(16)

By using the above formula (16), the skin lesion is separated from the normal skin that shows as the binary image.

**Levelset Model**

The region based levelset method was proposed by Margarida Silveira[13], which uses Gaussian probabilistic model for the image. Initially assume that the image is of two regions \( R_1 \) and \( R_2 \) and are separated by the curve \( C \). These regions are modeled by the probability density functions \( p_1 \) and \( p_2 \). Better segmentation is achieved by minimizing the energy function.

The energy function as follows,

\[
E(\varphi, p_1, p_2) = \int_B \delta(\varphi) \left| \nabla \varphi \right| dx - \int_B H(\varphi) \log p_1 + \left( H(\varphi) \right) \log p_2 dx
\]

(17)

Where \( H \) is a Heaviside function, \( H(z) = 1 \) for \( z > 0 \) and \( H(z) = 0 \) for \( z < 0 \). The evolution of \( \varphi \) is governed by the partial differential equation.
Wavelet Network Model

The wavelet Network model for melanoma segmentation is proposed by Amir Reza Sadri [15]. The Wavelet Network is of two types namely Adaptive Wavelet Network (AWN) and Fixed Grid Wavelet Network (FGWN). Fixed Grid Wavelet Network (FGWN) in [16] involves weight determination using linear estimation techniques. Its structure can be constructed by employing a ten-stage algorithm. Considering M input-output data as in the inputs matrix is the form \( X = [x^{(1)} \ldots x^{(k)} \ldots x^{(M)}] \). The output vector is considered as \( y = [y^{(1)} \ldots y^{(k)} \ldots y^{(M)}]^T \). The FGWN structure is determined by a ten-stage algorithm as follows:

Normalization: To avoid distributed data, normalization is performed as the first step. In cases of no symbolic data distribution, this step can be omitted.

Mother wavelet is selected by using multidimensional single scaling wavelet frame, desirable regularity and easy frame generation can be achieved for which multidimensional Mexican Hat Radial wavelet is employed for WN implementation. Choose Maximum and minimum scale levels and shift parameters.

Formation of wavelet lattice: This step focuses on calculation of wavelet function for all input vectors based on the prior step wavelet parameter space; using a hyper shape as shown in the Fig. 1.

Primary Screening: This step involves formation of a set for each scale level from the prior step.

Secondary screening: In this step a set \( I \) is constructed based on the wavelets shift and scale parameters from at least two sets from the prior step.

Formation of wavelet matrix: This step focuses on the matrix calculation for the chosen scale and shift parameters from the prior step and the input vectors [17].

Performing OLS algorithm: The matrix members of prior step can still be redundant as the output information is not considered while the input information is solely considered. The OLS algorithm provides a speedy as well as effective model structure determination approach. The algorithm proceeds in an iterative fashion wherein initially most significant wavelets are selected and the rest non selected wavelets are made orthogonal to the selected ones.

Selecting number of wavelons: The nodes that form the hidden layer are wavelons. The system performance index is calculated by selecting an ideal number of wavelons.

Calculating wavelons weight coefficient: The final step of the algorithm focuses on the weight calculation of wavelons using least-squares method by the equation

\[
Q \hat{Y} = A \hat{\theta}
\]  

Fuzzy C-means Clustering Algorithm

The Fuzzy C-Means (FCM) clustering algorithm was first introduced by Dunn [23] and later was extended by Bezdek [24]. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective function \( J_{FCM} \) [24]:

\[
J_{FCM} = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik})^q d^2(x_k, v_i)
\]

where \( X = [x_1, x_2, \ldots, x_n] \subseteq \mathbb{R}^p \) is the data set in the p-dimensional vector space, \( n \) is the number of data items, \( c \) is the number of clusters with \( 2 \leq c < n \), \( u_{ik} \) is the degree of membership of \( x_k \) in the \( i \)th cluster, \( q \) is a weighting exponent on each fuzzy membership, \( v_i \) is the prototype of the centre of cluster \( i \), \( d^2(x_k, v_i) \) is a measure between object \( x_k \) and cluster centre \( v_i \). A solution of the object function \( J_{FCM} \) can be obtained via an iterative process, which is carried out as follows:

1. Set values for \( c, q \) and \( \varepsilon \).
2. Initialize the fuzzy partition matrix \( U = [u_{ik}] \).
3. Set the loop counter \( b = 0 \).
4. Calculate the c cluster centers \( \{y_{i}^{(b)}\} \) with \( U^{(b)} \)
\[
y_{i}^{(b)} = \frac{\sum_{k=1}^{n} (u_{ik}^{(b)}) q x_{k}}{\sum_{k=1}^{n} (u_{ik}^{(b)}) q}
\] (21)
5. Calculate the membership \( U^{(b+1)} \). For \( k = 1 \) to \( n \), calculate the following:
\[
I_k = \{ i \mid 1 \leq i \leq c, d_k = \| x_k - v_{ik} \| = 0 \}
\] (22)
for the \( k^{th} \) column of the matrix, compute new membership values:
(a) if \( I_k = \varnothing \), then
\[
u_{ik}^{(b+1)} = \frac{1}{\sum_{j=1}^{c} (d_{ik} u_{jk})^{q-2}}
\] (23)
(b) else \( u_{ik}^{(b+1)} = 0 \) for all \( i \in I \) and \( i \in I_k, u_{ik}^{(b+1)} = 1 \); next \( k \).
6. If \( \| u_{ik}^{(b+1)} \| < \varepsilon \), stop; Otherwise, set \( b = b+1 \) and goto step 4

SEGMENTATION RESULTS AND EVALUATION
The performance of the above mentioned algorithms are evaluated based on the following metrics [18]. These metrics use the parameters namely True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). The figure illustrates the parameters. GA is a Ground Truth obtained from the dermatologist and SA is the segmentation done by the algorithm.

![Figure 3: Performance metrics parameters](image)

- Sensitivity
- Specificity
- Accuracy
- Border Error
- Mean Square Error
- Peak Signal To Noise Ratio (PSNR)
- Elapsed Time
- Hammoude distance

**Sensitivity**
It defines the proportion of positives measured as such.
\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\] (23)

**Specificity**
It defines the proportion of actual negatives which are correctly identified as such.
\[
\text{Specificity} = \frac{TN}{TN + FP}
\] (21)

**Accuracy**
It is the proportion of true results (both true positives and true negatives) in the population.
\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\] (22)

**Border Error**
It is the ratio of the area covered by the XOR of segmented result (SR) and ground truth (GT) images to the area covered by GT image.
\[
\text{Border Error} = \frac{FP + FN}{TP + FN}
\] (23)

**MSE**
It measures the average of the square of the difference between the segmented image and the original image.
\[
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (I_{seg} - I_{orig})^2
\] (24)

**PSNR**
It is a measure of reconstruction quality.
\[
\text{PSNR} = 10 \log_{10} \frac{\text{maximum intensity}^2}{\text{MSE}}
\] (25)

**Elapsed Time**
It is the total time taken to complete the program.

**Hammoude distance**
It makes a pixel by pixel comparison enclosed by the two boundaries.
\[
\text{Hammoude distance} = \frac{FP + FN}{TN}
\] (26)

**DISCUSSION**
The overall analysis of the above stated algorithms is as follows: The adaptive thresholding method is based on a different approach and adaptively changes the threshold value, depending on the local image properties. The result obtained by the adaptive thresholding shows that this will be suitable only if the color sensitivity of the dermoscopic images is optimum. It is further observed that the adaptive thresholding method has a tendency to generate nevus segments that are larger than their actual size. So the adaptive thresholding method exhibits very poor performance when the lighting condition is poor or non-uniform. Fuzzy based algorithms are based on the membership functions. Choosing of correct membership function is the challenging task. But it provides superior results to thresholding techniques. SRM technique provides acceptable performance even in noisy scenario [18]. This algorithm manages accuracy in segmentation to the optimum. Geometric deformable models are semi-automatic.
as the initial curves need to be defined manually to avoid negative influence from the complicated imaging background. So the robustness of the approach and study the influence of shape accuracy on the classification of the skin lesions are difficult one. The segmentation results were compared with those of the level set method using single Gaussian densities with fixed standard deviation, using manually obtained contours as the ground truth and obtained better results. But it needs the manual estimation of the number of mixture components. Wavelet based network model employs two stages of screening. This gives ground to increase the globablity of the wavelet lattice and to estimate the function in a more accurate way which is most beneficial and significant for larger scales. The main advantage of WNs over similar architectures such as multilayer perceptions (MLP) and networks of radial basis functions (RBF) is the possibility of optimizing the WN structure by means of efficient deterministic construction algorithms. Fuzzy C-Means clustering algorithm gives better results for overlapped data set and data point is assigned membership to each cluster center as a result of which data point may belong to more than one cluster center.

CONCLUSION
This paper evaluates and analyses the performance of the stated algorithms on dermoscopic skin lesions. The results show that each algorithm has unique and comparable features on their own. Choosing of suitable algorithm is a challenging task and based on the problem type. Overall results show that, SRM provides better performance even in noisy and worst lightning conditions and provides better accuracy in segmentation.

REFERENCES
Felsia Thompson was born in Veeyannoor, Tamilnadu, India on 1st April 1984. She studied her Masters in Computer Applications degree from Manonmaniam Sundaranar University, Thirunelveli, Tamilnadu, India in 2007. She received her Master of Philosophy in Computer Science from Vinayaka Missions University, Salem, Tamilnadu, India in 2009. Presently, she is a research scholar at the Department of Computer Applications, Noorul Islam Center for Higher Education, Noorul Islam University, Tamilnadu, India. Her research interest is Image Processing Applications.

Dr. M. K. Jeya Kumar was born in Nagercoil, Tamilnadu, India on 18th September 1968. He received his Masters in Computer Applications degree from Bharathidasan University, Trichirappalli, Tamilnadu, India in 1993. He fetched his M.Tech degree in Computer Science and Engineering from Manonmaniam Sundaranar University, Tirunelveli, Tamilnadu, India in 2005. He completed his Ph.D degree in Computer Science and Engineering from Dr.M.G.R University, Chennai, Tamilnadu, India in 2010. He is working as a Professor in the Department of Computer Applications, Noorul Islam University, Kumaracoil, Tamilnadu, India since 1994. He has more than twenty two years of teaching experience in reputed Engineering colleges in India in the field of Computer Science and Applications. He has presented and published a number of papers in various national and international journals. His research interests include Mobile Ad Hoc Networks and network security, image processing and soft computing techniques.