A Hybrid Dermoscopic Images Segmentation Scheme Using Fast FCM, DWT2 and YUV

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Abstract—Accurate diagnosis of the skin lesion boundaries is a difficult task even for an expert (experienced specialists). Thus automatic segmentation of dermoscopic images has been proposed in recent years. In this paper, a hybrid dermoscopic image segmentation method has been proposed which employs fast fuzzy c-mean, YUV and wavelet decomposition properties. In the proposed method, RGB image is converted to YUV color space and U channel after denoising is enhanced by applying contrast adjustment. Then, a primary segmentation image is obtained using statistical gray level histogram based fast version of fuzzy c-mean clustering. The final segmented image would be achieved after employing wavelet transformation, Otsu thresholding and morphological reconstruction algorithms. The experimental results reveal that the proposed scheme not only attains higher accuracy and sensitivity, also has lower false negative and positive errors in compared with the related existing methods.

Keywords—Dermoscopy Images, Fast Fuzzy C-Mean, Otsu Thresholding, Segmentation, Wavelet, YUV Color Space.

1. INTRODUCTION

Although cancer can develop from almost any cell in the body, certain cells are more cancer-prone than others. For the skin there is no exception. Most skin cancers develop from non-pigmented cells and not from pigmented melanocytes. Thus, the two most common skin cancers are basal cell carcinoma and squamous cell carcinoma, which develop from basal and squamous keratinocytes, accordingly. However, an aggressive malignancy of melanocytes, malignant melanoma, is a less common but far more deadly skin cancer. Melanoma is characterized by the most rapidly increasing incidence and causes the majority (75%) of deaths related to skin cancer. In its advanced stages (with signs of metastasis) melanoma is incurable, and the treatment, being solely palliative, includes surgery, immunotherapy, chemotherapy, and/or radiation therapy [1].

Pigmented skin lesions include both, benign and malignant forms [2]. Differentiating malignant and benign cases is a hard task even for experienced specialists [3]. Dermoscopy is a noninvasive diagnostic technique that consists in the examination of skin lesions with a dermoscope, which is a hand held optical device that typically consists of a magnifying lens and a light source, used to illuminate the skin [4]. Dermoscopy yields 10%—27% higher sensitivity than clinical diagnosis, significantly improving the accuracy of dermatologists when diagnosing melanoma. Yet, dermoscopic diagnosis remains subjective and is therefore associated with poor reproducibility [5]. Because of a computer-aided diagnosis system can be a useful tool [3].

The segmentation is the most important stage for analyzing image properly since it affects the accuracy of the subsequent steps. It is said to be fine if it segments the required region accurately and without any over segmentation [6]. However, proper segmentation is difficult because of the great varieties of the lesion shapes, sizes, and colors along with different skin types and textures. In addition, some lesions have irregular boundaries and in some cases there is smooth transition between the lesion and the skin [7]. In order to resolve the problems, several segmentation methods have been presented such as fuzzy c-means (FCM) clustering technique, thresholding, FCM thresholding based level set (LS), combined watershed & wavelet [8]-[12].

In [8] a dermoscopy image segmentation algorithm is introduced which is based on mean shift based fuzzy c-means method and incorporates a mean field term within the standard fuzzy c-means objective function. In [9] a segmentation method is proposed in which the median filter of size 7 is used for image denoising and the resulted image from preprocessing stage, is converted to grey scales. Then the Otsu method which is a technique based on pixel segmentation is applied on the preprocessed image. Then an opening operation (i.e. erosion followed by a dilatation) and afterwards, a closing operation (i.e. dilatation followed by an erosion) with structured elements of size 3 are applied to manipulated image. Finally connected components labeling with 8-connectivity applied to binary images to keep the biggest objects. In [10] a segmentation scheme is presented which combined fuzzy c-mean algorithm, thresholding and level set method. In this scheme 3-class fuzzy c-mean thresholding are applied to initialize level set automatically and estimate controlling parameters of their evolution. In [11] an algorithm is presented for automated segmentation of both normal and diseased brain MRI. Entropy driven homomorphic filtering technique is employed in this work to remove the bias field. The initial cluster centers are estimated by adaptive window and a modified fuzzy c-mean (MFCM) technique is applied using the neighborhood pixel considerations to segmentation of the image.

In [12], a technique is proposed which combined watershed transform and wavelet filters to segment the dermoscopic images. In this technique, eight types of wavelet filters are applied before watershed transform. The resulting image is then classified into two classes:
background and foreground. As watershed transform generated many spurious regions on the background, morphological post-processing is conducted in this work. Also, the post-processing split and merged spurious regions depending on a set of predefined criteria.

On the other hand, in statistical histogram based fast version of fuzzy c-means (FFCM), the iteration is carried out with the statistical gray level histogram of image instead of the conventional whole data of image. So its speed is higher than FCM [13]. In [14], [15] the authors have proposed two algorithms for image segmentation which are used FFCM.

In this paper, a hybrid dermoscopic image segmentation scheme has been proposed in which fast fuzzy c-mean, YUV and wavelet decomposition properties are employed. In the proposed method the image pixels are segmented in 2-classes: skin and lesion. Also wavelet transform and Otsu thresholding are used to improve FFCM results and achieve the binary image, respectively. The experimental results show that the proposed method satisfies dermoscopic image segmentation requirements such as increasing accuracy, sensitivity and decreasing FNE and FPE, more than existing methods in [8]-[12].

2. Basic Theories

A. Fast Fuzzy C-Means Algorithm

The fuzzy c-means (FCM) algorithm assigns pixels to each category by using fuzzy memberships. Let \( X = (x_1, x_2, ..., x_N) \) denotes an image with \( N \) pixels to be partitioned into \( c \) clusters. FCM is based on minimization of the objective function [16]:

\[
J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^m \| x_i - c_j \|^2 \quad 1 \leq m < \infty \tag{1}
\]

Where \( u_{ij} \) represents the membership of pixel \( x_i \)in the cluster \( j \), \( c_j \) is the \( j^{th} \) cluster center, \( m \) is the fuzzification factor which is a weighting exponent on each fuzzy membership, \( u_{ij} \) is any real number greater than 1. In the standard use of fuzzy c-means, the weighting coefficient \( m \) is set to \( m = 2 \) and \( \| \cdot \| \) is any norm expressing the similarity between any measured data and the center [17]. FCM computes the membership \( u_{ij} \) and the cluster centers \( c_j \) by [16],[17]:

\[
u_{ij} = 1/\left( \sum_{k=1}^{c} (\| x_i - c_k \|/\| x_i - c_j \|)^2 \right)^{1/(m-1)} \tag{2}
\]

\[
c_j = \left( \sum_{i=1}^{N} u_{ij}^m x_i \right) / \left( \sum_{i=1}^{N} u_{ij}^m \right) \tag{3}
\]

The FCM algorithm involves the following steps:
1) Set values for \( c \) and \( m \)
2) Initial membership matrix \( U = [u_{ij}] \), which is \( U^{(0)} \) \( |U| = \) number of members, \( |J| = \) number of clusters)
3) At k-step: calculate the centroids for each cluster through (3) if \( k \neq 0 \). (If \( k=0 \), initial centroids location by random)
4) For each member, calculate membership degree by (2) and store the information in \( U^{(k)} \).
5) If the difference between \( U^{(k)} \) and \( U^{(k+1)} \) less than a certain threshold, then stop; otherwise, return to step 3 [17].

Since FCM algorithm is an iterative operation, it is very time consuming which makes the algorithm impractical used in image segmentation. To cope with this problem, the gray level histogram of image is applied to the algorithm which speeds up the standard FCM algorithm [15]. When applied to image histogram segmentation, a fast version of FCM (FFCM) is preferred to conventional one due to its computational cost [18].

Define the non-negative integrate set \( G = \{ L_{\min}, L_{\min+1}, ..., L_{\max} \} \) as gray level, where \( L_{\min} \) is the maximum gray level, so the grayscale is \( L_{\max} - L_{\min} \). For image size \( S \times T \), at point \( (s,t) \), \( f(s,t) \) is the gray value with \( 0 \leq s \leq S - 1, 0 \leq t \leq T - 1 \). Let \( His(g) \) denote the number of pixels having gray level \( g \), \( g \in G \).

The statistical histogram function is as follows [14],[15]:

\[ His(g) = \sum_{j=1}^{S} \sum_{i=1}^{T} \delta(f(s,t) - g) \tag{4} \]

Where \( g = \{ L_{\min}, L_{\min+1}, ..., L_{\max} \} \), \( \delta(0) = 1 \) and \( \delta(g \neq 0) = 0 \). With the statistical level histogram, the new cost function defined as follows [18]:

\[ J_m = \sum_{g=0}^{L_{\max}-1} \sum_{j=1}^{c} (u_{ij})^m His(g) d^2(g,v_i) \tag{5} \]

By an optimization way similar to the standard FCM algorithm, the objective function \( J_m \) can be minimized under the constraint of \( U \) as stated in (4). The membership \( u_{ig} \) and the cluster centers \( v_i \) by [14]:

\[ u_{ig} = 1/\left( \sum_{j=1}^{c} (d_{ig}^m / d_{ij}^m)^{2/(m-1)} \right) \forall i, g \tag{6} \]

\[ v_i = \left( \sum_{g=0}^{L_{\max}-1} (u_{ig})^m His(g) \right) / \left( \sum_{g=0}^{L_{\max}-1} (u_{ig})^m \right) \tag{7} \]

The Fast FCM algorithm only operates on the histogram of the image and hence is faster than the conventional version which processes the whole data set. Thus, the computation of the membership degrees of \( His(g) \) pixels is reduced to that of only one pixel with \( g \) as gray level value [14].

B. Two Dimensional Wavelet Transform (DWT2)

The wavelet transform is a mathematical tool that can be used to describe images in multiple resolutions. The wavelet decomposition is a complete representation, since it allows a perfect reconstruction of the original image. Also, since a low-pass filter is involved, noise suppression is inherent to this transform [19]. According to Mallat’s pyramid algorithm, the input image is convolved with low-
pass and high-pass filters associated with a mother wavelet, and down sampled afterwards. Four images (each one with half the size of the original image) are produced, corresponding to high frequencies in the horizontal direction and low frequencies in the vertical direction \(HL\) (horizontal details), low frequencies in the horizontal direction and high frequencies in the vertical direction \(LH\) (vertical details), high frequencies in both directions \(HH\) (diagonal details) and low frequencies in both directions \(LL\) (approximation coefficients) [19], [20].

**C. Otsu Thresholding**

Otsu method is type of global thresholding in which it depend only gray value of the image. Otsu method was proposed by Scholar Otsu in 1979. Otsu method is global thresholding selection method, which is widely used because it is simple and effective. The Otsu method requires computing a gray level histogram before running. Otsu method uses an exhaustive search to evaluate the criterion for maximizing the between-class variance [22].

**D. YUV Color Space**

The YUV color space is widely used in video and broadcasting today. It is very different from RGB color space; instead of three large color channels, it deals with one brightness or luminance channel \(Y\) and two color or chrominance channels \(U\)-blue and \(V\)-red. The transform from RGB to YUV that retains the same number of colors in both spaces is [23]:

\[
\begin{bmatrix}
Y \\
U \\
V
\end{bmatrix} =
\begin{bmatrix}
0.299 & 0.587 & 0.114 \\
-0.147 & -0.289 & 0.436 \\
0.615 & -0.515 & -0.100
\end{bmatrix}
\begin{bmatrix}
R \\
G \\
B
\end{bmatrix} \quad (8)
\]

3. **PROPOSED FRAMEWORK**

The proposed hybrid dermoscopic image segmentation scheme includes three pre-processing, segmentation and post-processing steps. So that, in pre-processing step \(U\) channel of YUV color space is used because of its high clearness in showing the lesion and low past filtering (LPF) of fourier domain is used to denoise unwanted effects. As it was mentioned before, fuzzy c-mean has been shown to work well for clustering based segmentation, however due to its iterative nature the computational cost of the algorithm is relatively high compared to other segmentation techniques [8]. Thus, in segmentation step of the proposed algorithm, Fast FCM method is used to solve this problem. Moreover, wavelet transformation and Otsu thresholding are used to enhance primary segmentation of image pixels in 2-classes: skin and lesion. Also, in post-processing step, morphological reconstruction algorithms are used to increase the segmentation requirements such as sensitivity, accuracy and specificity. The block diagram of the proposed method is shown in Fig. 1 and detailed as follows:

1- Convert the dermoscopic image to YUV color space from RGB and select \(U\) channel as the target channel to achieve more accuracy of segmentation.

2- Apply LPF of fourier domain on \(U\) channel of converted dermoscopic image to denoise the effects of hair, skin lines, blood vessels, and air bubbles.

3- Enhance the contrast of denoised image using intensity adjustment.

4- Set the number of classes \(C\) (in (1)) to 2, to classify image pixels into two classes: 1) lesion and 2) background (skin), and apply the FFCM clustering algorithm to pre-processed image to achieve the primary segmented image. As it was mentioned before, this algorithm uses image histogram instead of all of image pixels. So it has higher speed than standard fuzzy c-mean.

5- Decompose the lesion image (class 1) into two-level wavelet.

6- Apply Otsu thresholding on each of four second level sub-bands of wavelet transform to obtain four threshold values: \(T1, T2, T3\) and \(T4\).

7- Add all of the threshold values and achieve new threshold \(T\).

8- Reconstruct the second level decomposed sub-bands and apply the new threshold \(T\) on the reconstructed sub-bands to obtain a binary image as follows:

\[
p(i, j) = \begin{cases} 
1 & r(i, j) > T \\
0 & \text{Otherwise} 
\end{cases}
\]

Where \(r\ (i, j)\) and \(p\ (i, j)\) respectively are the images pixel values of reconstructed from second level sub-bands and binary.

9- Determine the connected components and compute the area of each component to remove the small objects.

10- Fill holes in the binary image.

4. **ANALYSIS OF THE PROPOSED ALGORITHM AND EXPERIMENTAL RESULTS**

The proposed scheme has been conducted on
dermatoscopic images which belong to standard database from two university hospitals (University of Naples in Italy, and University of Graz in Austria). All cases were diagnosed on the basis of histopathological examination of biopsy material. The database that used for analysis include Clark nevus, Melanoma in situ, Melanoma (tumor thickness: TT less than 0.75mm), Reed nevus, Melanoma (0.75mm ≤ TT < 1.5mm), Melanoma (1.5mm ≤ TT) with manual extraction results by five expert dermatologists. The five expert dermatologists manually have drawn the border on the tablet computer [24].

All of the experiments were implemented using MATLAB R2011a and biorthogonal spline (B-spline) wavelet filters was used for computation of the wavelet transforms. Cause of using B-spline function wavelet is that, B-spline functions, do not have compact support, but are orthogonal and have better smoothness properties than other wavelet functions [25]. It has to be mentioned that, in post-processing step, all connected components (objects) that have less than 1057 pixels and were diagnosed as the lesion wrongly were removed from binary image and also the holes that were diagnosed as the background wrongly were filled and new binary image products.

In the experiments, five standard metrics: sensitivity, specificity, accuracy, false positive error (FPE), and false negative error (FNE) are employed.

A sensitivity measure is the proportion of actual lesion pixels that are correctly identified as such; specificity measures the proportion of background skin pixels that are correctly identified; and accuracy determines the true value, the repeatability or reproducibility of the measurement, the proximity of measurement to the precision results [21]. They are defined as follows [26], [27]:

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (11)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (12)
\]

\[
\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \quad (13)
\]

These three metrics define based on four parameters: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). To define these parameters, SR is the result of a segmentation algorithm and GT is the ground truth that it is segmentation of the medical expert. Both GT and SR are binary images [26].

TP is the number of pixels that were classified both by GT and SR as lesion pixels, \( TP = GT \cap SR \).

TN is the number of pixels that were classified both by GT and SR as non-lesion pixels, \( TN = (GU \cup SR) \).

FP is the number of pixels where a non-lesion pixel was falsely classified as part of a lesion by SR, \( FP = SR \cap GT \).

FN is the number of pixels where a lesion pixel was falsely classified as non-lesion by SR, \( FN = GT \cap SR \).

\[
\text{FPE}(SR, GT) = \frac{\#(SR \cap GT)}{\#(GT)} \quad (14)
\]

False negative error (FNE) determines the rate of pixels categorized as lesions by the medical expert that were not assigned as lesion by the automatic segmentation. It is defined as [10]:

\[
\text{FNE}(SR, GT) = 1 - \frac{\#(SR \cap GT)}{\#(GT)} \quad (15)
\]

To illustrate the quality of the proposed method, we have simulated it on 70 dermatoscopic images. The obtained results are shown in Figs. 2 and 3. As it can be found the proposed method satisfies segmentation requirements as well. So that, from Fig. 2, it can be seen that the minimum percentage of sensitivity is 79.08, all of specificity values are greater than 89.49% and the minimum percentage of accuracy is equal to 90.26; and from Fig. 3, it can be seen that, the maximum percentage of FPE and FNE are respectively equal to 18.73 and 20.91. In addition, the percentage of average values sensitivity, specificity and accuracy on all 70 segmented dermatoscopic images are respectively equal to 93.26, 97.78 and 96.00.

![Fig. 2. The obtained results of sensitivity, specificity and accuracy in all 70 segmented dermatoscopic images](image-url)
The obtained results of FPE and FNE in all 70 classes: skin and lesion. Also, to increase the ONCLUSIONS processing step, U channel of YUV color space is used. The segmented images in the worst conditions and processing step. The experimental results able. 1, it could be find that the proposed method satisfies sensitivity and accuracy properties more than all three works in [9], [11], [12] and has higher specificity values in comparing with [9]. Also, from Table 2, it could be found that the proposed scheme has lower FPE and FNE values in comparing with the both works in [8], [10].

Table 1: The compression results of the proposed scheme in Accuracy, Sensitivity and Specificity

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Methods</th>
<th>%</th>
<th>%</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>78.72</td>
<td>75.92</td>
<td>88.6</td>
<td>93.26</td>
</tr>
<tr>
<td>Specificity</td>
<td>94.26</td>
<td>99.52</td>
<td>98.21</td>
<td>97.78</td>
</tr>
<tr>
<td>Accuracy</td>
<td>87.14</td>
<td>92.12</td>
<td>94.61</td>
<td>96.00</td>
</tr>
</tbody>
</table>

Table 2: The compression results of the proposed scheme in FPE and FNE

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Methods</th>
<th>%</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[8]</td>
<td>6.52</td>
<td>13.75</td>
</tr>
<tr>
<td></td>
<td>[10]</td>
<td>4.66</td>
<td>7.34</td>
</tr>
<tr>
<td></td>
<td>proposed</td>
<td>2.45</td>
<td>7.30</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

Due to the segmentation has important rule in automatic diagnosis of skin lesions, in this paper a hybrid dermoscopic image segmentation scheme in which in the pre-processing step, U channel of YUV color space is used because of its high clearness in showing the lesion and low past filtering (LPF) of fourier domain is used (LPF) to denoise unwanted effects: hair, skin lines, blood vessels, and air bubbles. In segmentation step, FFCM method, wavelet transformation and Otsu thresholding are used to solve the problem of high computational cost of the FCM and enhance the primary segmentation of image pixels in 2-classes: skin and lesion. Also, to increase the segmentation requirements such as sensitivity, accuracy and specificity, morphological reconstruction algorithms are used in post-processing step. The experimental results indicate that the proposed method not only satisfies the segmentation requirements as well, rather has higher average percentage of sensitivity, specificity and accuracy in comparing with the works in [9], [11], [12] and lower average percentage of FPE and FNE in comparing with the works in [8], [10].

REFERENCES