Automatic Mobile Segmentation of Dermoscopy Images Using Density Based and Fuzzy C-Means Clustering

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***Abstract*—Accurate identification and extraction of region of interest (ROI) in dermoscopy images play crucial role in diagnosis, and treatment of melanoma and other skin diseases. Human interpretation of dermoscopy images is not only tedious and time consuming task but also subjective. This fact has attracted numerous attentions for developing automated assessment tools. In this paper, we present lesion detection schemes in dermoscopy images on mobile platforms. The systems are based on density based clustering (DBSCAN) and fuzzy c-means (FCM) clustering and developed for Windows Phone and Android environments. We tested the systems on dermoscopy images and ROIs are successfully extracted. The proposed systems may improve the management of melanoma by providing automatic early monitoring of skin lesions that will assist clinical investigation.**

I. Introduction

Identifying and extracting the region of interest (ROI) is an important step in many medical image segmentation applications [1], [2]. Among many others, faster transmitting diagnostic medical images requires high level ratio of compression for effective use of bandwidth and energy consumption. ROI must be compressed by lossless or near lossless algorithm while on the other hand, the background region must be compressed with some loss of information that is still recognizable [3].

Another application of image segmentation is in analysis and early diagnosis of the skin lesion in digital environment. It has been agreed that early diagnosis is very important for most of the cancer types and it is not different for malignant melanoma. Malignant melanoma is the most deadly form of skin cancer. It is the fifth most common type of new cancer diagnosis in American men and the seventh most common type in American women. In 2011, it is estimated that 70,230 individuals are diagnosed with melanoma in the United States, and 8,790 people die as a result of the disease [4]. Approximately $1.9 billion is spent in the United States each year on melanoma treatment [4], [5].

Early diagnosis of malignant melanoma is based on examination of the skin lesions. Fortunately, if malignant melanoma is detected in early stages, it is almost always curable. However, if not caught early, melanoma is often fatal [6]. Thus, early detection of cancerous skin lesion is very crucial in terms of both treatment and economic perspectives. Figure 1 shows border detection of a dermoscopy image.

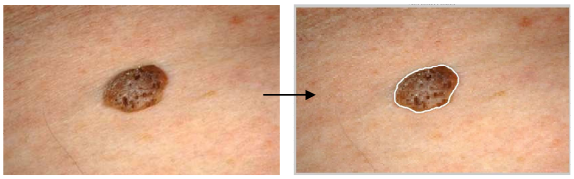

Fig. 1: Segmentation of a dermoscopy image [3].

Generally, there are 2 general clinical diagnosis approaches for malignant melanoma which are both based of characteristics such as color, shape, dimension and texture: ABCD rule and 7-points checklist [7], [8]. Clinical diagnosis approaches also depend on the features like asymmetry, border irregularity, shape and dimension properties. Therefore, interpreting dermoscopic images including detection of skin lesion outline has a great potential for the early diagnosis of malignant melanoma. Since this interpretation is subjective and time consuming, developing automatic dermoscopic image analysis system to help clinical determination is currently of a great interest.

Methods of image segmentation for skin lesion can be grouped as region based approaches, thresholding based approaches, contour based approaches and edge based approaches. Region based techniques [9], [10] aims dividing an image into regions based on certain image properties. Thresholding based approaches [11] rely on the classification of different regions of an image according to the intensity values of image pixels. In contour based methods [1], [2], [3], [12], [13], segmentation starts with a curve around the object to be detected and continues until the curve reaches an optimal position guided by external constraints. Edge based approaches [14], [15] classify the image pixels as edge or non-edge applying an edge filter and then segmented region is obtained by removing the outlier edge points.

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In recent years, there is an increasing interest in bringing computer vision algorithms to work on mobile environment. Due to their mobility and portability, mobile devices have the potential to develop various new generation applications using computer vision algorithms. Detection of skin lesion could also find use in mobile phones that can help self-monitor diagnosed malignant melanoma. Developing a mobile framework for segmentation of dermoscopy images to examine skin lesions would be very beneficial in diagnosis of melanoma in terms of cost, time, and reliability. In this work, we present a mobile based system for the segmentation of dermoscopy images. The proposed system can be used to support clinical determination by providing automatic early screening of skin lesions. The user can capture an image of the interested region of the skin and the image is processed to detect skin lesion using density based clustering (DBSCAN) and fuzzy c-means (FCM) clustering. We developed the system on the Windows Phone and Android platforms. The remainder of the paper is organized as follows: In Section II and Section III, lesion detection frameworks are described on Windows Phone and Android environments, respectively. In Section IV, results of our approach as well as applications on the Android and Windows Phone platforms are presented. Finally, in Section V, the conclusions and future research of this study are summarized.

II. Windows Phone based Lesion Detection

Figure 2 shows the flowchart diagram of the system relying on [16] for Windows Phone platform. The original dermoscopy image captured via mobile device is in RGB (red-green-blue) space. However, lightness component of HSL (hue-saturation-lightness) model represents intensity values of the color image which is more relevant for detection purpose [17], [18]. We therefore converted each pixel of RGB space to L, lightness channel of HSL using [19]:

$$L = \frac{\max(\mathrm{R},\mathrm{G},\mathrm{B}) + \min(\mathrm{R},\mathrm{G},\mathrm{B})}{2} \quad (1)$$

To extract skin lesion from the resulting grayscale image, simple intermeans technique is used [20]. An optimum threshold is computed iteratively for cleaner segmentation of the skin lesion. The algorithm starts with an initial guess of threshold, i.e. median pixel value. Then, mean pixel values for both greater and equal or less than the initial threshold are calculated. The average of these two means is computed and truncated to an integer value which gives the next threshold. The iteration continues until the stopping criteria is reached, i.e., until the threshold stops changing from one iteration to the next.

To group black pixels on the binary image generated by intermeans algorithm, DBSCAN [21], [22] is used. DBSCAN is designed for discovering cluster of arbitrary shapes and successfully used for different type of datasets. The algorithm [21] adopted for the lesion segmentation is given as follows:

```
DBSCAN (BinaryImage, Eps, MinPts)
  ClusterId := nextId(NOISE);
  FOR i FROM 1 TO BinaryImage.size DO
    Point := BinaryImage.get(i);
    IF Point.ClId = UNCLASSIFIED THEN
      IF ExpandCluster(BinaryImage, Point,
        ClusterId, Eps, MinPts) THEN
        ClusterId := nextId(ClusterId)
      END IF
    END IF
  END FOR
END;
```

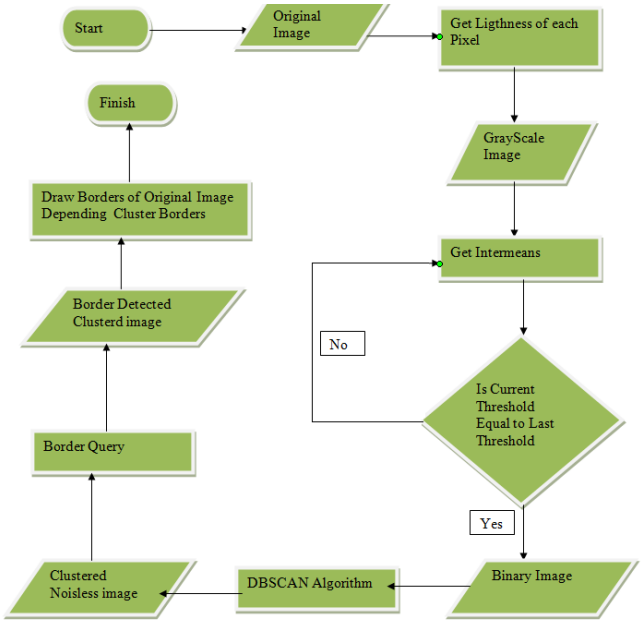


Fig. 2: Flowchart diagram of the system.

The algorithm has two parameters, namely Eps and $MinPts$, and clusters the pixel points depending on the distance between each other. Starting with an arbitrary point p, a cluster is formed by searching points no less than $MinPts$ in a circle neighborhood of point p with radius Eps. If the number of points in the neighborhood is less than $MinPts$, the point p is labeled as a noise. This procedure is repeated for all points of binary image.

Figure 3 summarizes the process of extracting lesion region. First, an original RGB dermoscopy image (Figure 3a) is converted to the grayscale image containing pixels defined by lightness component of HSL space (Figure 3b). Then, binary image is generated from the grayscale image based on intermeans algorithm (Figure 3c). Finally, the pixels of binary image are clustered using DBSCAN algorithm to segment the lesion region (Figure 3d).

III. Android based Lesion Detection

An overview of the Android based lesion detection system is depicted in Figure 4. The system has two-step process to extract a lesion from a dermoscopy image: (i) preprocessing which includes median filtering and contrast enhancement, and (ii) thresholding with FCM clustering.

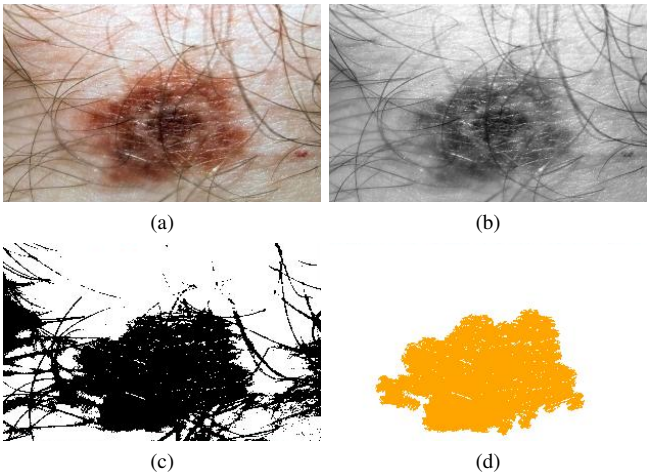


Fig. 3: Extraction of lesion region: a) original dermoscopy image in RGB space, b) grayscale image created with lightness channel, c) binary image produced by intermeans algorithm, d) clustered pixels resulted from DBSCAN.

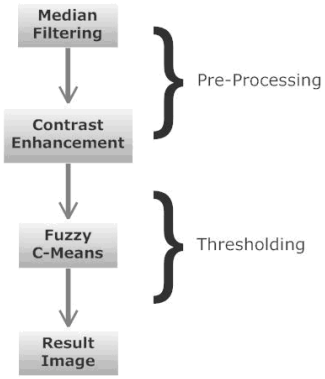


Fig. 4: Overview of the Android based system.

First, a 3×3 median filtering is applied in red, green, and blue channels of the original RGB image. Median filtering is very useful for the removal of the noises and preservation of the edges. The neighboring pixels of 3×3 window are ranked according to their intensities and the median value is assigned to the new value of the central pixel. Second, contrast enhancement is performed to improve the information visibility. Histogram equalization [23] is applied to the grayscale dermoscopy image converted from RGB space in order to increase global contrast. It flattens the image's histogram by transforming the intensity image based on the probability distribution of the input intensity values. Finally, FCM clustering is used to segment the lesions. FCM clustering technique [24], [25] allows each data point to belong to more than one cluster instead of just one cluster. Flowchart diagram of the algorithm is given in Figure 5. The aim of the algorithm is that the objective function must be minimized and is written in the following form:

$$\min \quad \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{2}$$

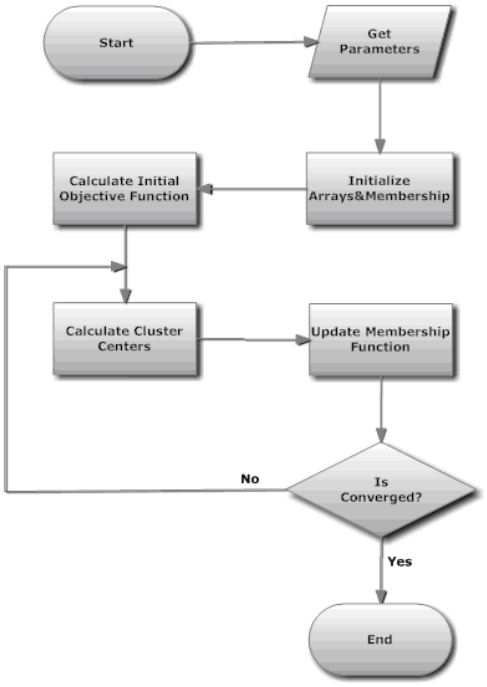


Fig. 5: Flowchart diagram of the algorithm.

where m is the fuzzification factor which is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the i^{th} of d-dimensional measured data, c_j is the dimension center of the cluster, and $\|.\|$ is the Euclidean distance between any measured data and the center.

Given an initialization $U^{(0)}$ for initial membership matrix $U = [u_{ij}]$, the membership u_{ij} is updated as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}} \tag{3}$$

At k-step, cluster centers c_j for center vector $C^{(k)} = [c_j]$ with $U^{(k)}$ is calculated as:

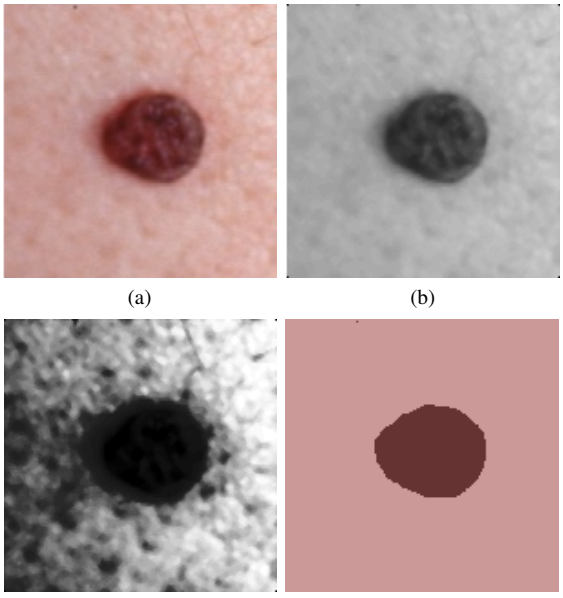
$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{4}$$

The computation of membership function is carried out successively until the difference of consecutive membership is less than a certain threshold, i.e., 1.

Figure 6 summarizes the lesion segmentation process based on FCM clustering. First, dermoscopy image in RGB space (Figure 6a) is preprocessed with median filtering (Figure 6b) and contrast enhancement (Figure 6c). FCM clustering is then employed on preprocessed image to extract the lesion (Figure 6d).

IV. Results

In this section, we present lesion segmentation of dermoscopy images on Windows Phone and Android platforms.



(a) (b) (c) (d)

Fig. 6: Segmentation of lesion: a) original dermoscopy image in RGB space, b) median filtered image, c) contrast enhanced image with histogram equalization, d) lesion extracted using FCM clustering.

Windows Phone based system was implemented under Microsoft Visual Studio using Windows Phone SDK, while Android based system was developed on Eclipse Indigo using Android SDK. Figure 7 and Figure 8 show application interfaces on the Windows Phone and Android emulators, respectively. The interfaces support the user in determining parameters of the algorithms. Windows Phone interface allow the user to specify Eps and $MinPts$ parameters of the DBSCAN algorithm. Contrast enhancement amount and FCM parameters including fuzzification factor, number of classes and threshold value are user inputs on the Android interface.

Fig. 7: Windows Phone interface.

Some segmentation results based on DBSCAN for Windows Phone are given in Figure 9. Eps value of 5 and $MinPts$ value of 75 are used in our experiments. Fuzzification factor and threshold value are taken as 2.0 and 40, respectively, with 15% contrast amount and 2 classes in experiments of Android segmentation using FCM (Figure 10).

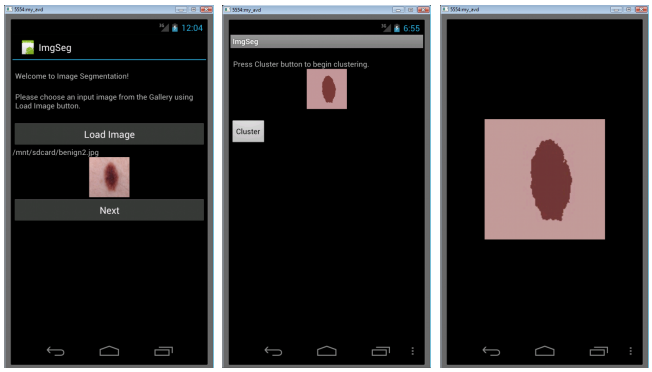


Fig. 8: Android interface.

From the obtained results, we can find that the lesions in dermoscopy images are successfully segmented as a region of interest on the mobile environment. We are currently building a ground truth of dermatology images whose borders are manually drawn by dermatologists for a more thorough evaluation of our mobile systems.

V. Conclusion and Future Work

Due to the subjectivity of human interpretation in dermoscopy images for detection of melanoma, there has been a growing interest in the development of automated systems to help clinical diagnosis. In this paper, we presented mobile frameworks automating the process of lesion detection in dermoscopy images. The presented frameworks are developed on the Windows Phone and Android environments. Windows Phone based system uses DBSCAN to detect lesions and FCM is employed in Android based system to segment lesions. The systems are experimented on dermoscopy images and our results show that our approaches are able to segment lesions correctly. The proposed computer aided segmentation framework paired with mobile platform offers cost-effective and non-invasive solution in diagnosis, and monitoring of melanoma. In order to further extend this work, we will examine dermatology images with dermatologist-drawn boundaries of lesions for a quantitave comparison.

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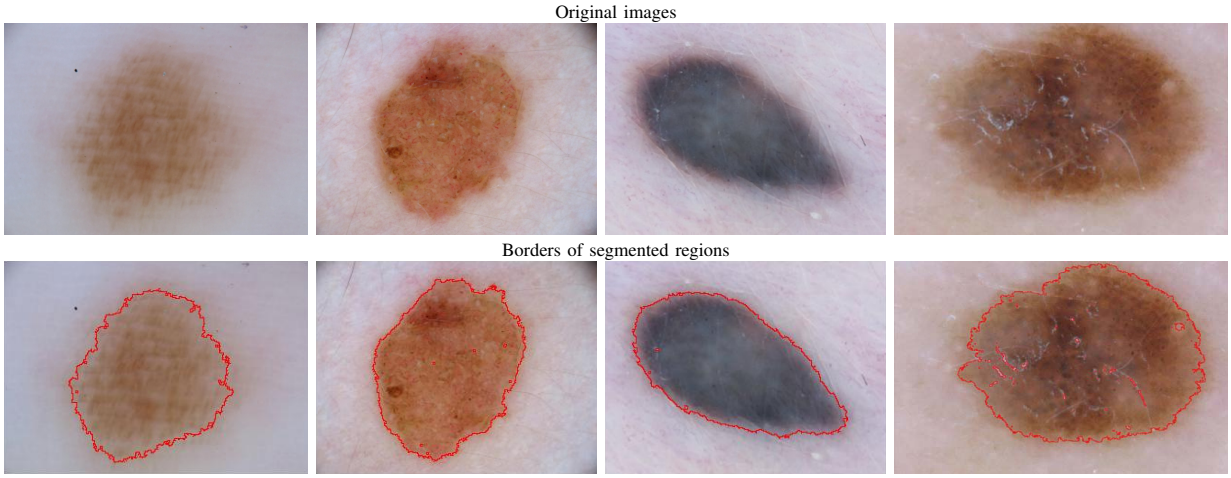

Fig. 9: Windows Phone segmentation by DBSCAN.

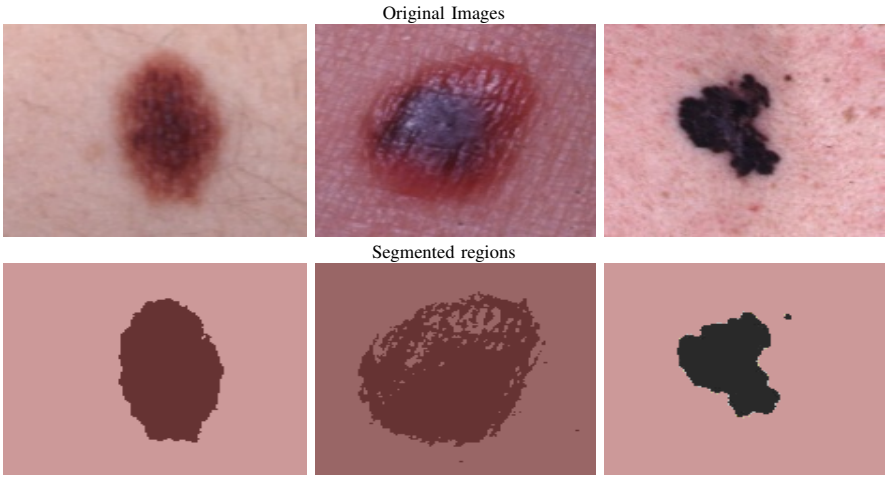

Fig. 10: Android segmentation using FCM.

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