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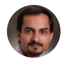
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# Detection and Classification of Acne Lesions in Acne Patients: A Mobile Application

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***Abstract*—Acne is a common chronic skin disease involving blockage and/or inflammation of hair follicles and their accompanying sebaceous gland. Acne can present as non-inflammatory lesions, inflammatory lesions, or a mixture of both, affecting mostly the face but also the back and chest. Detecting the different types of acne lesions is important in both diagnosis and management. According to acne face mapping, presence of acne in various parts of the face or body has different indications for disease. In this paper, we present several image segmentation methods to detect acne lesions and machine learning methods used to distinguish different acne lesions from each other. Our results illustrated that among texture analysis, k-means clustering, HSV model segmentation techniques, two level k-means clustering outperformed the others with an accuracy of about 70%. In addition, the accuracy of differentiating acne scarring from active inflammatory lesions is 80% and 66.6% for fuzzy-c-means and support vector machine method, respectively. Finally, the performance accuracy of classifying normal skins from detected acnes is 100% using fuzzy-c-means clustering.**

## I. Introduction

Acne is a skin disease that affect oil glands with inflammation or infection [1]. It affects 85% of adults at some time during their lives [1]. To assess acne, clinicians and dermatologists use methods such as ordinary flash photography and direct visual assessment [2]. Occasionally, these methods can be time-consuming. In the treatment of acne, accurate evaluation of the severity of acne is important. Acne lesions can be classified into several skin types, including comedone, pustule, reddish papule, with or scarring without. However, in some cases, detecting acne from color image visually can be difficult for the proper evaluation of acne lesions.

To address these problems, recently researchers have proposed computational imaging methods for acne diagnosis. For example, Ramli *et al.* applied k-means clustering using color features [3]. The results of segmentation from randomly selected images illustrated the sensitivity, positive predictive value, specificity, and negative predictive value greater than 81%. Batool *et al.* took advantages of bimodal Gaussian mixture model (GMM) to distinguish Gabor features of normal skin from skin imperfections [4]. To combine the spatial connections among adjacent pixels for their GMM distributions and texture orientations, a Markov random field model (MRF) is used. Then, an Expectation-Maximization (EM) algorithm distinguished smooth skin from skin with wrinkles/imperfections. Malik *et al.* used the CIE La*b* color space to segment skin colors [5]. Segmentation of acne has been performed by using support vector machines (SVM) classifier and automated modified K-means clustering algorithm. To classify acne into different classes such as mild, moderate, severe, and very severe, diameter and color were extracted as the main features. The severity of detected acne then is diagnosed [5]. Fujii *et al.* proposed an extraction method by applying a combination of several linear discriminant functions (LDF's) to classify acne lesion types [6].

Most of the previous work detected the skin lesion which is taken from very close view with high resolution, in which there is only one acne lesion in each image. However, in this application, images that are used are from different parts of the body with low resolution and contain more than one acne lesion, which makes the problem more challenging.

The objective of this research is to find a proper computational imaging method for automatic detection of acne using images that are taken by cell phone and then the classification of the different type of acne lesions from each other.

## II. Methods and Materials

### *A. Data Acquisition*

In this study, images of various dermatology resources were used. For evaluating the methods, 35 images were used to perform the segmentation and classification of the different types of acne lesions such as comedone, red papule and pustule. Comedone occurs when hair follicles get plugged with oil and dead skin cells. Scarring is a fibrous process that occurs when new collagen is laid down to heal a full-thickness injury including inflammation. About 30% of those with moderate or severe acne vulgaris have scarring.

### *B. Image Processing*

In this study, we tried three different image processing methods on images our image database and compared the results. All the procedure were done using MATLAB 2015a

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software. These methods are:

*1) K-means clustering*

K-means aims to partition N observation to k clusters. The value of K can be given. Suppose there is a data set {x1,. . . ,xN} containing of N examples (observation) of a random D-dimensional Euclidean variable x. This method clusters the data in which inter-point distances of a group of data points are smaller compared with the distances to points outside of the cluster. To formalize this notion, we assume a prototype, $\mu_k$, associated with the *Kth* cluster. These prototypes are representing the centers of the clusters. Then the goal is to find the center of each cluster such that the sum of the squares of the distances of each data point is a minimum to its closest cluster center $\mu_k$[7].

The objective function, sometimes called a *distortion measure*, is given by

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} \|x_n - \mu_k\|^2 \qquad (1)$$

which characterizes the summation of the squares of the distances of each data point to its center.

The goal of segmentation using this method is to divide an image into regions, each of which has a rationally similar visual appearance or that matches objects or parts of objects. Each pixel in an image is a point in a 3-dimensional space comprising the intensities of the RGB components, blue, red, and green, and the segmentation procedure simply considers each pixel in the image as a distinct data point [7].

In this work, we took advantage of two-level k-means clustering that is a modified version of "Color-Based Segmentation Using K-Means Clustering" code. Before applying k-means clustering, first the RGB image was converted to the LAB color space. In the first level clustering, two classes were assigned: skin and acne lesions. For the second k-means clustering, three categories were assigned; from these three categories, our desired class is acne. In this method, after performing the first level of clustering, the user chooses the desired cluster for executing the second level.

*2) Texture Analysis*

Texture analysis characterizes regions and parts in an image based on their texture features. Texture analysis attempts to quantify features such as rough, silky, smooth, or bumpy as a function of the spatial variation in pixel intensities. In this application, the background (skin) is smooth; there is tiny variation in the gray-level values. In the foreground, the contours of acne exhibit more texture. In other words, foreground pixels have more variability and thus higher range values. Therefore, 3-D Gaussian methods have been used to smooth the image, and then the rangefilt MATLAB command was applied to compute the local range of the image.

*3) Color-based Segmentation (HSV model)*

There are different color scape models in image processing, such as RGB, HIS, and HSV. HSV is one of most the common cylindrical-coordinate models. This model rearranges the geometry of RGB to get more perceptually relevant and intuitive representation. HSV contains three components of hue, saturation, and value, and is also often called HSB (B for brightness).

The advantage of HSV over RGB is that HSV has more meaningfully components related to the psychological perception of color than RGB. For example, to segment green color in the HSV model, all the greens from lightest color to darkest, to least saturated to the most saturated pixel, have the same hue. However, in RGB model, if the image is filtered by Green > a, a certain amount of green pixels will be selected and dark greens will be missed. To perform HSV-based segmentation, a modified version of "Color Blob Utility with Automatic Thresholding and Tolerance Calculations" was used. In addition to these three methods, watershed segmentation and multi thresholding were applied, but failed to detect acne properly.

## C. *Classification of Images*

*1) Differentiation of skin with acne from skin without acne*

To classify images with no acne (normal skin) from acne images, a total of fifteen images were used (five healthy images, five images with acne scarring, and five with active acne lesions). The fuzzy c-means (FCM) method was utilized for this task.

FCM is a technique of clustering which allows a group of data to belong to two or more clusters. That is, instead of assigning group of data to one group, it assigns a group of data to two or more clusters. In this method, each cluster has the initial center and membership degree. By using an iterative optimization of the objective function, fuzzy partitioning was performed, with the update of the center of each cluster and then membership degrees.

*2) Classification of Acne Scarring from inflammatory Acne*

Another classification task was distinguishing acne scarring from inflammatory acne using Support Vector Machine (SVM) with linear kernel and fuzzy c-means method. SVM usually is used for binary (two class) classification using linear models of the form

$$y(x) = w^T \phi(x) + b \qquad (2)$$

where $\phi$ (x) denotes a fixed feature space transformation, and we have made the bias parameter b explicit. The concept of support vector machine is through of the margin. This margin is defined as the minimum distance between the decision boundary and any of the pixels (samples). In this machine learning technique, the decision boundary is chosen in which the margin is maximized [7].

In this task, five images of detected acne scarring and five images of detected inflammatory acne lesions were used.

## D. *Scoring Different types of Acne*

Although no grading system has been accepted universally, some studies have tried to find a proper criteria for grading acne lesions [3,8,9]. Previous works suggest only counting acne on one side of the face since it established that the number of lesions of the left side was nearly equal to those on the right. Eruption usually is divided into three categories: comedones; inflammatory eruption-included papules and pustules, and severe eruptions that included cyst and nodules.

Previous research shows that the photography-based results agreed with at least two of three expert results with an accuracy of 68.7%. The regression between lesion counting and classification of consulted dermatologist is r=0.68. Table 1 illustrates a comprehensive acne grading criteria, which is called "The Global Acne Grading System" [3].

TABLE 1 THE GLOBAL ACNE GRADING SYSTEM [3].

| Location | Factor (F) | Severity (S) | Local Score (F × S) |
|---|---|---|---|
| Forehead | 2 | 0: Nail | Mild: 1-18 |
| Right Cheek | 2 | 1: Comedone | Moderate: 19-30 |
| Left cheek | 2 | 2: Papules | Severe: 31-38 |
| Nose | 1 | 3: Pustule | Very Severe > 39 |
| Chin | 1 | 4: Nodule | |
| Chest and upper back | 3 | | |

## III. RESULTS

### A. Segmentation results

The results of detecting acnes using three different segmentation methods are shown in Figures 1, 2 and 3. Based on visual assessment, we got more than 70% accuracy in differentiating acnes from the skin by using 2 level k-means clustering.

### B. Classification results

In this study, we used two machine learning classification methods. We applied each classification method ten times. For SVM, the supervised method, 10-fold cross-validation was used. The average accuracy of classification to distinguish acne scarring from inflammatory acne for FCM and linear SVM methods were 80% and 66.6%, respectively. In the classification of normal skin from people with acne using FCM method, the performance accuracy is 100%.

## IV. DISCUSSIONS AND CONCLUSION

Although the texture method that is used in this study is not sufficient and needs improvement, HSV methods and k-means techniques got acceptable results in many cases. Comparing two level k-means clustering with HSV method, clustering method outperformed the color-based method. In the classification task, we used results of the best segmentation method, k-means clustering, to classify the images. The two level k-means clustering increased the accuracy of segmentation; however, in some cases, some detected acne lesions in the first level were wrongly classified to the other clusters in the second level.

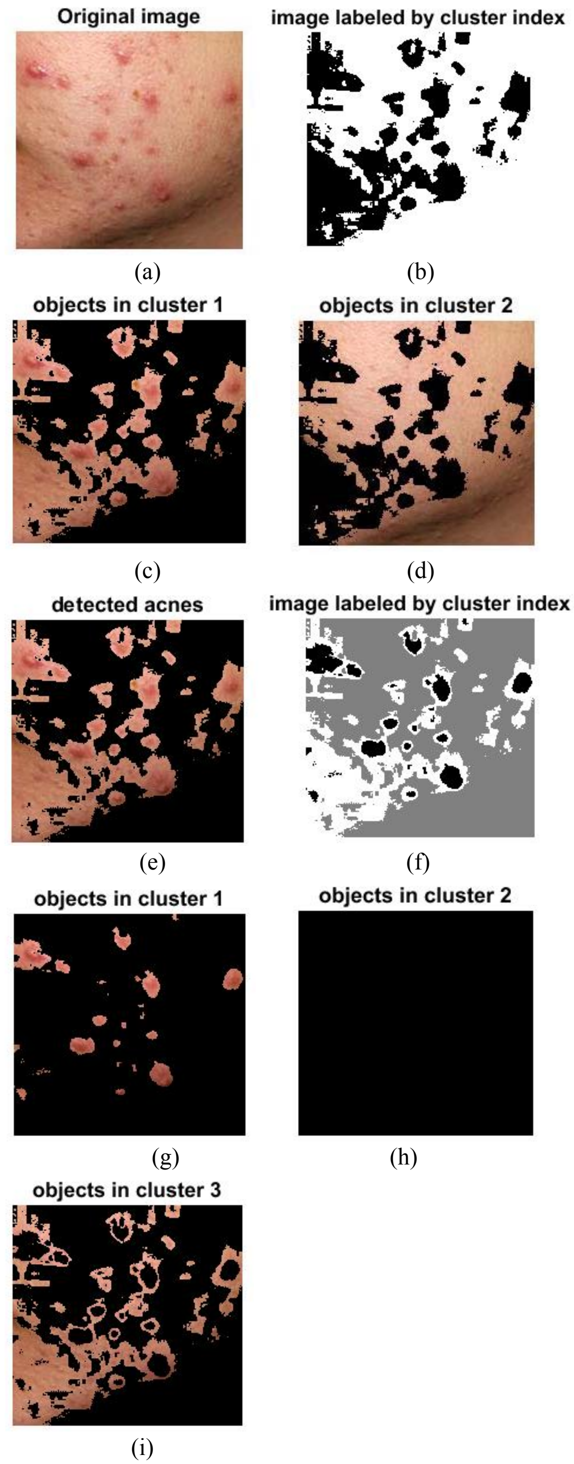


Fig 1. Results of two level k-means clustering. (a) the original image, (b) image labels by cluster index, (c) object in cluster one (which is used for second level of clustering), (d) object in cluster two, (e) selected cluster from first level to perform the second level of clustering, (f) image labeled by second level clustering, (g) object in cluster one which is detected acnes (our desired image), (h) object in cluster two (the background), and (i) is objects in cluster 3 which is skin that wrongly detected as acne in the first level clustering

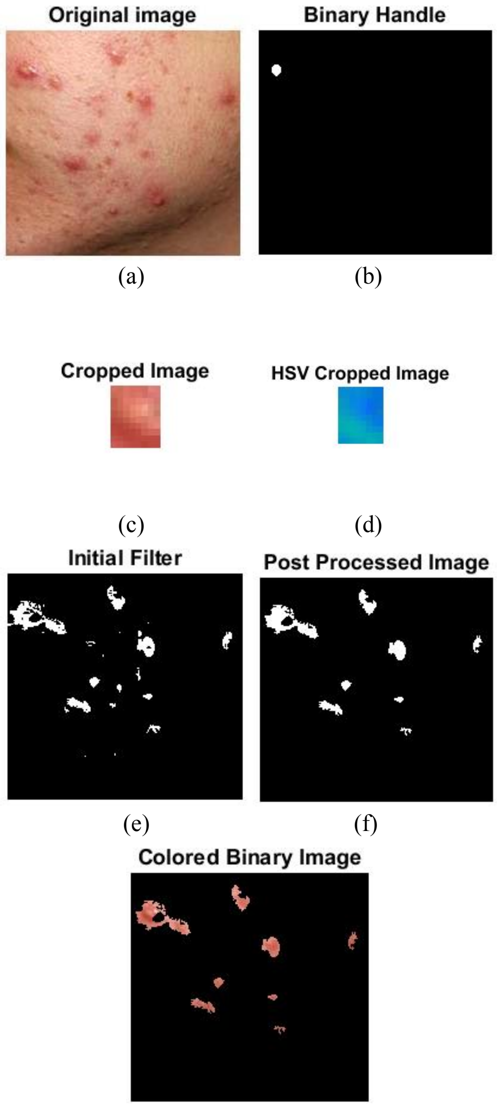


Fig 2. Results of color-based segmentation (HSV model). (a) Original image, (b) binary of the region which was selected by the user, (c) corrupted selected region in RGB color space, (d) corrupted image in HSV color space, (e) Initial filtering of original image using different thresholding for hue, saturation and value, (f) result of post-processing by filling any hole and getting rid of noise less than 20 pixels, and (g) the final detected colored binary image.

Using cell phone images to detect acnes can help in many applications. Nevertheless, there are some drawbacks of using photography to compute severity of acne [10]. Some of these disadvantages are:

1. Visualizing the small lesion is difficult.
2. Unlike palpation, it is hard to ascertain the depth of involvement.

Measuring constant lighting, distance between the patient and camera, and developing the procedure is difficult. There are different methods to segment acnes which were not used in this study. These methods are compression-based methods, histogram method, dual clustering, region-growing, graph partitioning methods such as Markov random fields, and watershed transform.

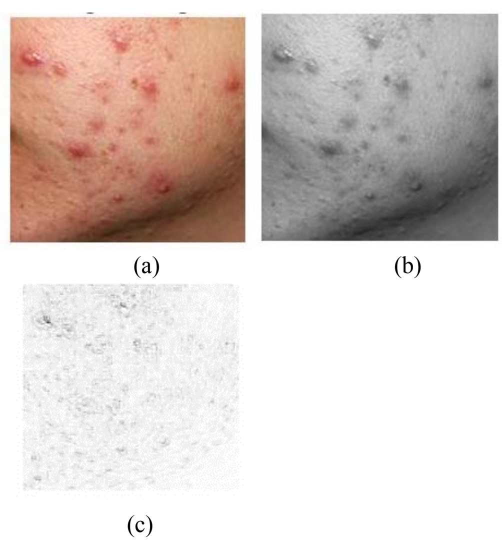


Fig. 3 Results of texture analysis. (a) Original image, (b) smoothed image using 3-D Gaussian filtering, and (c) is the after computing local range of image.

One idea for future research can be applying these methods to acne images and comparing the results and combining the successful algorithms to get higher accuracy to segment and distinguish acne types. In addition, in this study, we used a limited number of images to perform the segmentation and then classification tasks; however, there is a need for more images from more subjects taken by cell phone to evaluate the applicability of using cell phone application to detect the different acne lesions. Also, a specific rule should be defined for taking photos. For example, the size of all images should be the same (512 by 512), 8-bit grayscale resolution (256 possible intensity level per color band (RGB), and with a resolution of 24 bits per pixel.

The presence of other structures in the image such as hair and extraneous artifacts can greatly reduce the accuracy of detection of acne lesions. Moreover, different people have different skin color tone [11]; therefore, a relative color concept needs to develop. These modifications and enhancement can help to equalize any variations caused by photography/printing, lighting, or digitalization process, since the human visual system is based on a relative color system [11].

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