Segmentation of Skin Cancer Images

First A. Padmapriya Nammalwar, Second B. Ovidiu Ghita, and Third C. Paul F. Whelan

***Abstract*— The aim of this study is to provide an efficient way to segment the skin cancer images. A novel method is proposed that combines colour and texture for the segmentation of skin lesions from unaffected skin region in an image. The distributions of colour and texture features provide a good discrimination of skin lesions. The evaluation of the proposed method was based on the comparison with the Live Wire segmentation results. The segmentation results are evaluated quantitatively by means of a comparative experiment on a set of skin cancer images. The results indicate that the developed methodology proved effective and efficient for the skin cancer image segmentation.**

***Keywords*—** Colour, Melanoma, Segmentation, Skin cancer, Texture.

I. Introduction

Skin cancer is the most prevalent form of human cancer. Over exposure to sun is the cause of skin cancer. Skin cancer is a malignant tumor of the skin. There are different types of skin cancer and some are likely to be fatal. Skin cancers can be classified into melanoma and non-melanoma. Melanoma is a malignancy of the cells which give the skin its colour (melanocytes). The two most frequent types of non-melanoma skin cancer are Basal Cell Carcinomas and Squamous Cell Carcinoma. In addition, there are a number of other less common skin cancers including Merkel cell tumors, cutaneous lymphomas, and sarcomas [1]. Melanoma is the most dangerous form of skin cancer. It can spread through the whole body and is usually fatal if it does. If detected early, the cure rate for melanoma is almost 100 percent. Late detection, when the melanoma is more than three millimeters deep, results in only a 59 percent survival rate. Melanoma's are much less common than non-melanoma's, but they account for most of the mortality from skin cancers.

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Detection of malignant melanoma in its early stages considerably reduces morbidity and mortality [2]. Early detection also saves hundreds of millions of money that is spent on the advanced disease. People are considered more at risk if they have lots of moles, are fair skinned with blue eyes, tend to sunburn easily or have freckles [3]. The rate of melanoma cases worldwide is increasing faster than any other cancer, with an annualized rate of increase of six percent. While in the thirties of the century one out of hundred thousand people living in the United States or Europe suffered from melanoma. This number has risen to fifteen out of hundred thousand nowadays with the tendency still increasing [4].

Clinical features of pigmented lesions suggestive of skin cancer are known as the ABCD's of the skin cancer:

- Asymmetry
- Border irregularity
- Colour variation
- Diameter greater than 6mm

There are various image analysis techniques developed to measure these features. During the last years, a significant improvement in early tumor recognition has been achieved by using the epiluminescence microscopy (ELM). This technique uses oil immersion to render the epidermis translucent thus giving insight into subsurface structures of the skin which are not visible otherwise. This delivers a set of new features which have turned out to improve the reliability of early diagnosis considerably. The ELM criteria used by dermatologist for the classification of pigmented skin lesions are briefly outlined as follows [5]:

- Pigmentation - Asymmetry of pigmentation is indicative of malignant lesion.
- De-pigmentation - Represents absence or diminution of pigment within a pigmented lesion. In benign lesions, de-pigmentation is regular and usually found at the center, whereas in malignant lesions it is irregular located anywhere in the lesion, and found at the periphery.
- Colour - Irregular bluish or grey-blue areas can almost exclusively be found in malignant lesions.
- Brown Globules in benign lesions - They are uniform in size and shape and regularly distributed, whereas variations in size and shape and irregular distribution indicate malignity.
- Black Dots - When present in benign lesions, they only occur at the center and are regular in size, shape and distribution. In malignant lesions they also occur at the periphery, vary in size and shape, and are irregularly distributed.

Measurement of image features for diagnosis of the skin cancer requires the detection of lesions and localization in an image. It is essential to determine the lesion boundaries accurately so that measurements such as maximum diameter, irregularity of the boundary, and colour characteristics can be accurately computed. As a first step in skin cancer identification, the lesion boundaries are delineated by various image segmentation techniques. In this research work, colour and texture information from an image is used for the segmentation of lesion boundaries. The distributions of the texture and the distributions of the colour discriminated the colour texture image. The segmentation helps to diagnose the skin lesions in the early stages. The skin cancer images obtained from references [3] are in graphics interchange format (gif). They were converted to bitmap format to apply the segmentation procedure. Fifteen skin cancer images were considered for the application database.

II. DESCRIPTION

A. Factors Concerning the Segmentation

Various factors that affect the segmentation of skin cancer images are as follows:

- The skin lesions have complex structure, large variations in size as well as complex colours in the skin.
- The lesion is contrast to the surrounding skin.
- The borders of lesions are not always well defined.
- The influence of small structures, hairs, bubbles, light reflection, and other artifacts.
- The influence of the skin lesions in the surrounding regions.

These factors make the segmentation more complex. To analyze skin lesions, it is necessary to accurately locate and isolate the lesions. The description of the border aspect appears to be an important feature for clinical judgment [6]. Some border descriptors, such as border irregularity and the presence of abrupt border cutters have been considered as predictors of malignancy. Also, the variation in colour signifies the malignancy of the lesion. Hence effective discrimination of the skin lesions was based on the distribution of texture and colour features in this study. A pre-processing step was adopted to remove the influence of skin lesions in the surrounding regions and also the influence of small structures, hairs, bubbles etc.

III. FRAMEWORK FOR SKIN CANCER IMAGE SEGMENTATION

A novel way of combining texture and colour information's for the colour texture segmentation was developed that makes the segmentation robust and efficient for different types of images. The steps followed in this method are outlined below:
Initially the features were extracted using feature extraction techniques, in which image information is reduced to a small set of descriptive features.

- The LBP/C features are extracted from the average of the three planes in RGB colour space.
- The distribution of the texture features are used for texture discrimination.
- A Modified-Kolmogorov Smirnov (M-KS) non-parametric statistical test is used as a similarity measure to discriminate the texture distributions.
- A hierarchical splitting method is used to split the image based on the texture descriptions using the similarity measure.
- An adaptive smoothing is performed to preserve the features and to obtain a good segmentation along the boundaries. This technique used as a preprocessing to remove noise and prevent over segmentation.
- An unsupervised k-means clustering algorithm is performed on the image to obtain the distribution of the colour clustered labels.
- Distribution of the texture features and the distribution of the colour clustered labels are used to describe the texture and the colour respectively.
- The distributions of colour and texture were used to derive the merger importance value between two adjacent regions. The MI value was calculated using the M-KS statistic. Weights are included automatically to both texture and colour features in the histogram and are computed using the histograms of the colour labels.
- An agglomerative merging procedure based on the merging criteria determines the similarity between two different regions using M-KS statistic, producing the segmented image.
- The final step is to refine the boundaries of the image. A boundary refinement algorithm based on the colour histograms enhances the segmented result to obtain the final segmented image.

The different techniques adopted were detailed in the following sections.

A. LBP texture feature distributions

The LBP concept developed by Ojala et al. [7] attempts to decompose the texture into small texture units. A texture unit is represented in a 3×3 neighbourhood which generates 28 possible standard texture units. In this regard, the LBP texture unit is simply obtained by applying a simple threshold operation using the following rule:

$$E_i = \begin{cases} 0 & V_i < V_0 \\ 1 & V_i \geq V_0 \end{cases} \quad (1)$$

where V_0 is the central pixel of the 3×3 mask. The LBP is determined as follows:

$$LBP = \sum_{i=1}^{8} E_i \times 2^{i-1} \quad (2)$$

As the LBP does not take into consideration the contrast of he texture which is a measure of local greyscale variation, often the LBP is used in conjunction with a contrast measure. Here, the contrast measure is the normalized difference between the grey level of the pixels with a LBP value of 1 and the pixels with a grey-level 0 contained in the texture unit.
The distribution of the LBP/C of the image represents the texture spectrum. The LBP/C distribution is a 2D histogram of size $256\times b$, where b is the number of bins for contrast

measure. As suggested by Ojala et al. [7] we have used 8 bins for contrast measure (our experiments confirmed that best segmentation has been achieved when 8 bins have been used to sample the contrast measure). This 2D histogram is used as a texture discriminating feature in our implementation.

B. LBP colour feature distributions

This study uses the unsupervised clustering technique based on the *k*-means algorithm to cluster the colour features. The *k*-means algorithm [8] is the simplest and most popular among the iterative clustering algorithms. The k-means algorithm organizes the objects into an efficient representation that characterizes the population being sampled. The number of clusters is generally image dependent so the initial guess is 10 clusters, this number is sufficient to capture all the relevant clusters. The distribution of the colour clusters is used for colour description.

C. Modified Kolmogorov Smirnov (M-KS)

A nonparametric test M-KS statistic was used for comparing LBP/C with colour clustered labels. This tests the hypothesis that two empirical feature distributions have been generated from the same population. M-KS has the desirable property that it is invariant to arbitrary monotonic feature transformations [9]. The M-KS statistic is defined as the sum of the absolute value of the discrepancies between the normalized cumulative distributions.

$$D(s,m) = \sum_{i=0}^{n} \left| \frac{F_s(i)}{n_s} - \frac{F_m(i)}{n_m} \right| \quad (3)$$

where $F_s(i)$ and $F_m(i)$ represents the sample cumulative distribution functions; n_s and n_m represents the number of pixels in the sample regions. Since M-KS is normalised, it is advantageous over other statistical measures such as: G-statistic and the Chi square statistic.

D. Adaptive Smoothing

Various smoothing techniques are widely considered for different purposes in computer vision. The nonlinear smoothing preserves important features and also removes noise. Adaptive smoothing is a nonlinear smoothing which adapts pixel intensities to the local attributes of an image on the basis of discontinuity measures. The feature preserving adaptive smoothing algorithm proposed by Chen [10] was adopted, where the local and contextual discontinuity measures were jointly used. The advantage of this smoothing technique is that the parameters in the given adaptive smoothing algorithm critically determine the smoothing process. The parameters preserve the edges and removes noise. This procedure was used to prevent over segmentation.

E. Split and merge segmentation method

The segmentation method followed is based on a split and merge computational model [11]. The first step involves recursively splitting of the image hierarchically into four sub-blocks using only the LBP/C data. In this regard, the similarity measure between the resulting four sub-blocks is evaluated using the M-KS. The uniformity of the region is evaluated by a decision factor as follows:

$$R = \frac{MKS_{max}}{MKS_{min}} > X \quad (4)$$

where MKS_{max} and MKS_{min} are the highest and lowest M-KS values resulting after calculating the pair-wise M-KS values of the four sub-blocks and X is a split threshold value. The splitting process continues until the stopping rule is satisfied or the block size is smaller than a predefined value (for this implementation the minimum block size has been set to 16 $\times$16). During the splitting procedure for each block two distributions are computed, the LBP/C distribution and the distribution of labels contained in the clustered data. Note that the splitting decision evaluates only the LBP/C M-KS values.

The second step applies an agglomerative merging procedure on the image resulting after splitting in order to join the adjacent regions that have similar characteristics. This procedure calculates the merging importance (MI) between any adjacent regions in the split image and the adjacent regions with the smallest MI value are merged. The MI value between two adjacent regions is calculated as follows:

$$MI = w_1 \times MKS_1 + w_2 \times MKS_2 \quad (5)$$

where w_1 and w_2 represent the corresponding weights for LBP/C histogram and colour histogram respectively and the MKS_1 and MKS_2 are the MKS statistics for texture (LBP/C) and colour histograms in the two adjacent regions. These adjacent regions are also referred to as the sample and model regions The weights are automatically detected using an uniformity factor defined as the maximum of the ratio between colour clustered histogram and number of pixels in the two regions under consideration, the sample and the model regions.

$$k_j = \max\left\{ \frac{Clust_j[i]}{N_p} \right\} \quad (6)$$

where k_j represents the uniformity factor for the sample and the model regions respectively. If the difference between k_1 and k_2 is less than 0.1, i.e., both the sample and the model weights are more or less the same, then

$$w_2 = (k_1 + k_2)/2 \quad (7)$$

and

$$w_1 = 1 - w_2 \quad (8)$$

This indicates that colour influences more than texture, hence colour statistic is given more importance. On the other hand, if the difference between k's is high, both the texture and the colour are given equal weights. This method followed a simple stopping rule,

$$Min(MI) > Y \quad (9)$$

where Min(MI) represents the minimum merger importance value. If this is greater than a threshold value then the merging procedure is halted.

The agglomerative merging procedure resulted in blocky segmented image. A new boundary refinement algorithm was developed and used for the improvement at the boundaries between various regions. A pixel is regarded as a boundary point if it is on the boundary of at least two distinct regions, i.e., its region label is different from at least one of its four neighbours. For an examined point *P*, a discrete square with a dimension *d* around the pixel was placed and the colour

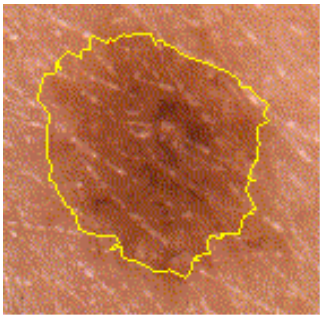
histogram for this region was computed. The corresponding colour histograms for the different neighbouring points were calculated. The homogeneity of the square region and the *i*th neighbouring region, *i*=1,2,...*l*...*n* region was computed. The pixel is reclassified if the MI value between adjacent regions and the region around the pixel under consideration is lower than the merge threshold. This procedure is iterative and proceeds until no pixels are relabelled. Reassigning pixels this way improves the accuracy of the segmentation process.

IV. Live wire segmentation

The evaluation of the proposed colour texture segmentation method was based on comparing the segmentation results with that of Live Wire segmentation results. In image segmentation, there are often situations when automatic segmentation techniques fail or lead to a suboptimal solution. As a consequence, an expert has to correct results manually. For interactive segmentation, an effective strategy is to exploit the synergy between a human operator who is superior in object recognition and an algorithm which is better in exact object delineation. The interactive Live Wire [12] algorithm utilizes methods from graph theory for achieving these abilities. An image constitutes a directed graph where the pixel vertices are graph nodes and oriented pixel edges represent edges of the graph. Graph edges are weighted with costs which are derived from image gradient magnitude and direction information. The basic problem of finding a boundary segment is therefore converted to finding a minimum-cost path between start and end of the segment. To find this optimal path, dynamic programming is used. A detailed explanation of the Live Wire segmentation can be obtained from reference [13].

V. Results and discussion

The proposed segmentation method was tested based on the experiments using skin cancer images. 15 different representative skin lesion images were used for testing. The images consist of different skin lesions such as malignant melanoma, basal cell carcinoma and squamous cell carcinoma. The skin cancer images used were of varying size. It is observable that the lesions have large variations in size as well as in colour and contrast to the surrounding skin. In some skin cancer images, hairs surrounding the skin lesion can be observed, which would have disturbing influence on the deviation of the correct boundaries.



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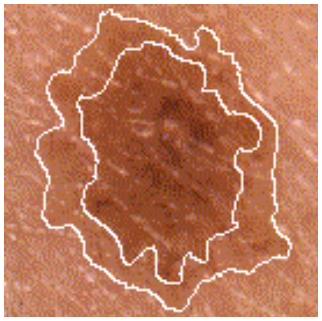

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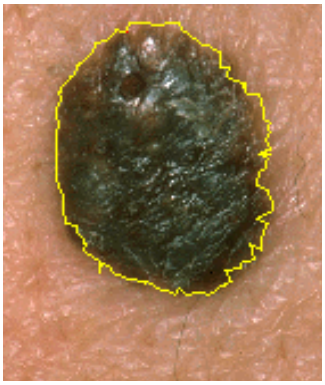

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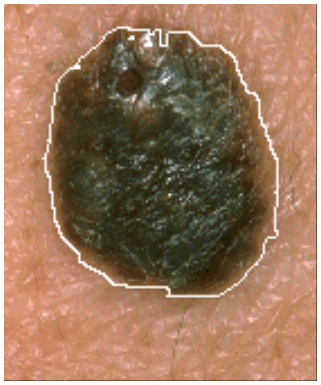

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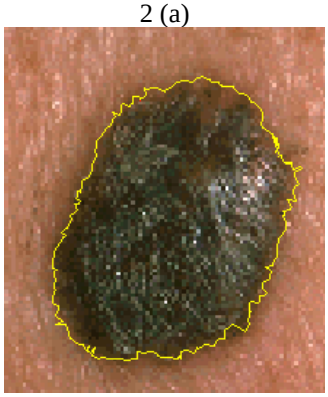

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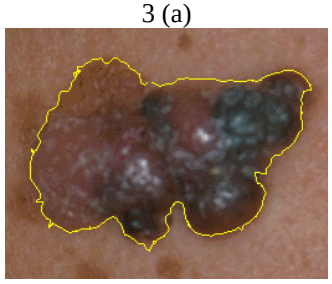

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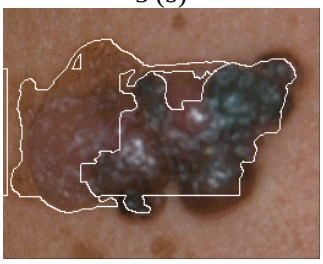

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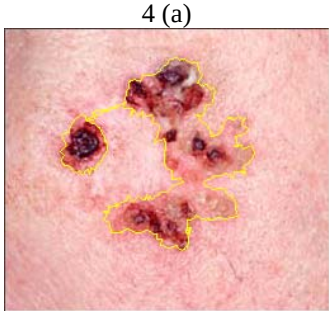

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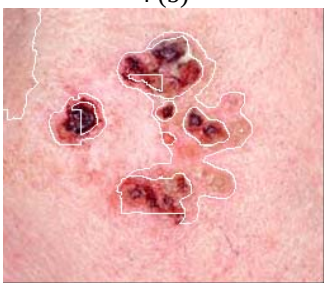

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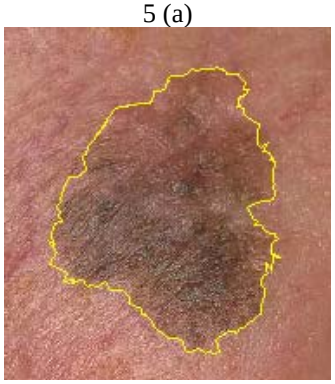

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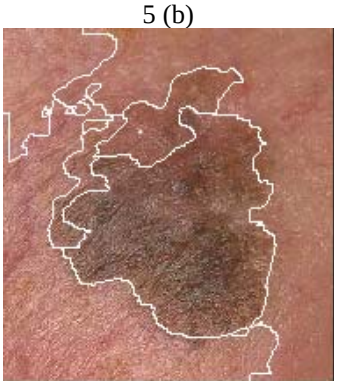

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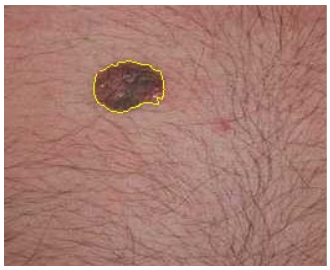

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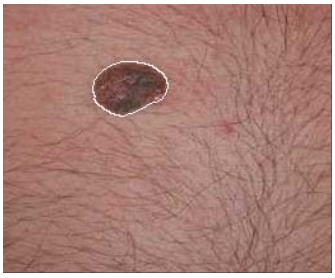

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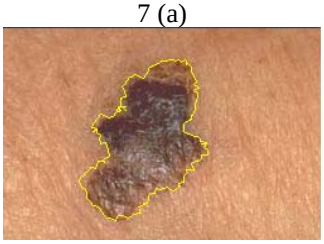

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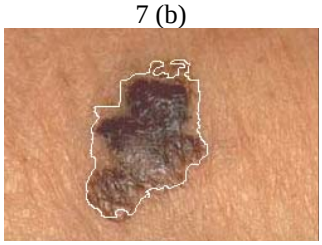

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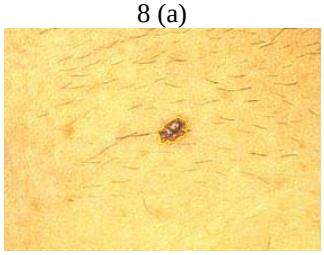

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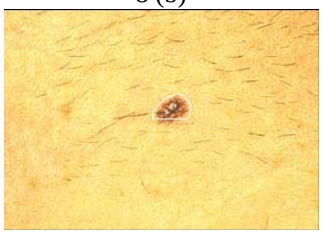

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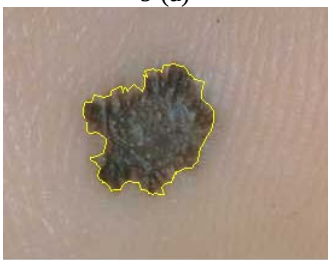

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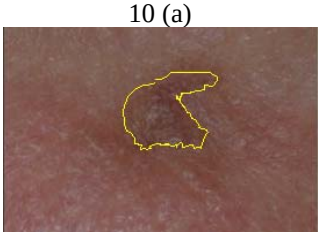

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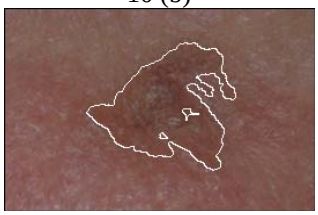

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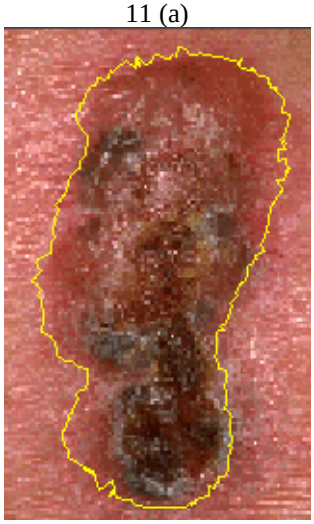

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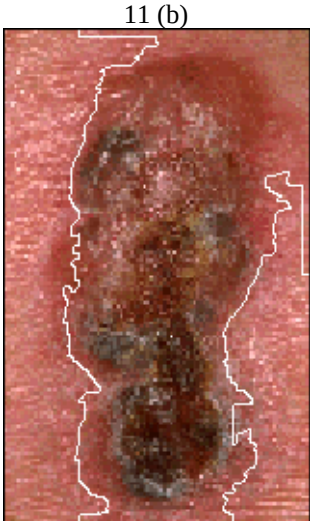

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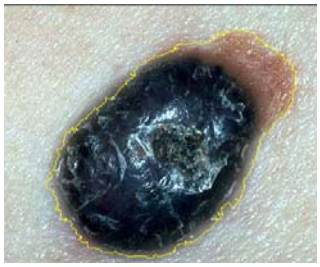

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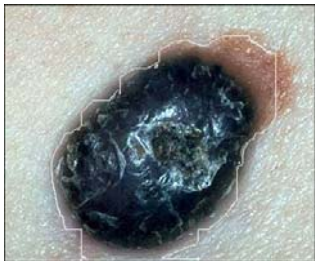

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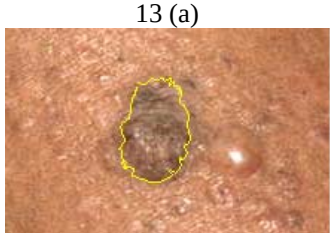

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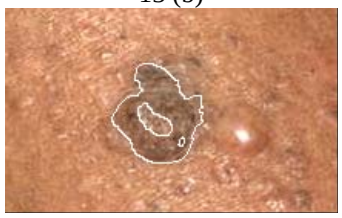

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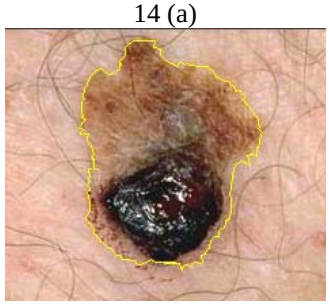

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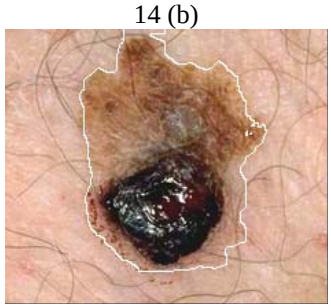

15 (b)

Fig 1-15. (a) Segmentation using Live Wire (b) Segmentation using colour texture distribution

Colour is one of the significant features in the examination of skin lesion. Typical examples of lesions show reddish, bluish, grey and black areas and spots. The fine variation in the colour is identified and segmented accurately. The distribution of texture and colour features presents significant information, hence the segmentation based on the two features is appropriate. This allows the isolation of lesion from healthy skin and extracts homogeneous coloured regions separately. The boundary obtained with Live Wire segmentation is shown in Fig 1.a. The boundary obtained with colour texture segmentation is shown in Fig 1.b. The colour texture segmentation resulted in two boundaries based on the colour gradient present in the image. Similar segmentation results were obtained in Fig 2.a and Fig 2.b by using the two methods. It is evident that the colour change is significant within a few pixels. In Fig 3.b, the boundary appears larger than the boundary obtained from the Live Wire method. The presence of a colour gradient along side the original boundary leads to the inclusion of few pixels around the lesion. Fig 4.b shows the detection of the regions within the lesion due to the difference in colour. In Fig 5.b, a small region at the left top corner is incorrectly segmented due to the colour difference. Similarly, in Fig 6.b additional regions were created where the transition from the lesion to the surrounding skin is very smooth. The skin cancer image in Fig 7.a and Fig 7.b shows accurate segmentation results by both the methods. The disturbances that could be anticipated due to the presence of hairs were overcome by using the adaptive smoothing procedure to obtain the best result. On the other hand, the non use of preprocessing resulted in the identification of the hairs

in the skin. Similarly, Fig 8.a and Fig 8.b illustrates an example for a good segmentation in both Live Wire and colour texture segmentation. In Fig 9.a and 9.b similar segmentation results were obtained. Though the proposed segmentation method was able to identify the lesion, the normal skin with two different coloured regions was also segmented. The role of dermatologist is very important for such an image. Fig 10.a and Fig 10.b illustrates a proper segmentation result. The detection of lesion boundaries by Live Wire method is complex in image such as Fig 11.a but Fig 11.b illustrates an acceptable result by colour texture segmentation. Fig 12.b shows segmentation with extended boundaries. Fig 13.a and Fig 13.b demonstrates the segmentation using Live Wire and colour texture respectively. In this image, the proposed method was able to identify the lesion boundary though there is a variation in colour. Fig 14.a and 14.b shows a good segmentation, but the disturbances such as bubbles in the skin were overcome by using the pre-processing. Fig 15.b considers the different coloured regions in the skin lesion as a single region. This is due to the minimum textural variation in the image.

Based on the authors' visual assessment, the boundaries obtained using colour texture segmentation is comparable with the boundaries obtained using Live Wire segmentation. The overall impression was that the two techniques used to identify skin lesions gave results with acceptable boundaries. It is interesting to note that for some images the Live Wire segmentation is different from that of the colour texture segmentation due to colour variation. This raises the question as to where the actual boundaries are, and it appears that different experts use different rules to segment an image. A complete validation can only be performed from expert results by a dermatologist. A more objective impression of the performances of the segmentation and boundary detection schemes can be obtained using a statistical comparison with boundaries drawn by hand by expert dermatologist. The experimental results obtained proved to be encouraging and indicate that the proposed method for colour texture segmentation is appropriate to be applied for detection of skin cancer. The efficient performance of the proposed colour texture segmentation method recognized the boundaries in the skin lesions exactly.

VI. Conclusion

This work presents a method for the segmentation of skin cancer images. The segmentation method is based on the colour and the texture present in the skin cancer images. The distribution of colour features and the distribution of the texture features were used for colour texture discrimination. The distribution of the derived features encompasses both the structural pattern and the colour of the image. This isolates the accurate boundaries of the skin lesions.

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