SET OF DESCRIPTORS FOR SKIN CANCER DIAGNOSIS USING NON-DERMOSCOPIC COLOR IMAGES

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ABSTRACT

Melanoma is the deadliest form of skin cancer. Diagnosis of melanoma in early stages significantly enhances the survival rate. Recently there has been a rising trend in web-based and mobile applications for early detection of melanoma using images captured by conventional cameras. These images usually contain fewer detailed information in comparison with dermoscopic (microscopic) images. Meanwhile, non-dermoscopic images have the advantage of broad availability. In this paper a set of ten features is proposed which cover different color characteristics of melanoma visible in skin images. The first 5 features are extracted using Fuzzy C-means clustering based on color variations and color spatial distributions of pigmented skin. These features are shown to be discriminative for melanoma lesions. The next 5 features consider colors and intensity of the colors. Hence, a 10 dimensional color feature space is formed. Experimental results show that classification accuracy of suspicious moles, by the proposed set of features, outperforms comparable state-of-the-art methods.

Index Terms—Melanoma diagnosis, feature extraction, pigmented skin lesion, medical imaging, classification

1. INTRODUCTION

Melanoma is the most aggressive kind of skin cancer [1]. Its rate of incidence has recently been growing, increasing on average by 2.6% per annum in the U.S. [2]. Despite the great danger that it poses, early stage melanoma is highly curable. There is 98% chance of survival for early diagnosis and only 17% chance of survival of distance stage cases [3].

In early stages, melanoma appears very similar to other benign melanocytic skin lesions, so numerous clinical metrics for early detection of melanoma are employed such as ABCD (asymmetry, border irregularity, color patterns, and diameter) [4] and the seven-point checklist [5]. Many computer assisted diagnosis methods exist for proper estimation of these clinical criteria in dermoscopic images (images taken by special skin microscope, called dermoscope) such as [6] and a review is given in [7].

Recently there has been an emerging trend for utilizing conventional user-grade cameras for computer assisted melanoma diagnosis [8-12]. Analyzing images of suspicious skin lesion by standard camera specifically is noticed in areas of telemedicine, mobile and web-based applications due to ease of access. However, digital images contain less detailed information as compared to dermoscopic images and usually are subjected to illumination and noise effects.

In [8] a decision support system is proposed that for the final estimation of lesion malignancy it combines extracted features of the skin image with some side-information from the patient, such as age and location of the affected regions. The proposed classification in [9] and [10] are based on set of low level features for estimation of ABCD criterion in standard cameras. Works of [11] and [12] are two of the most recent researches in this field. In [11], set of high level intuitive features for assessment of the role of ABCD is proposed and results are evaluated on ideal manually segmented lesion for final performance measurement of the features. In [12], illumination correction and segmentation is automatically done on the input image and some color and texture features are extracted. In addition, they use a physician's annotations of the images and the final classification is done by voting between three criteria of color, texture, and annotations. Furthermore [13, 14] are example of commercial applications that are publically available and claimed to be based on imaging and pattern recognition methods evaluating the ABCD metric.

In this paper we aim to assess the importance of color cue in the melanoma diagnosis. We propose new color based features regarding specific melanoma aspects that are extractable from non-dermoscopic images. Firstly some preprocessing is applied to reduce noise and illumination effects that usually exist in digital skin images. Segmentation is done on preprocessed image to separate regions of lesion from healthy skin. Afterward, a set of 10 proposed features are extracted to differentiate between cancerous (melanoma) and benign moles. These features specifically consider color variation, spatial color distribution and intensity and color values. Finally these discriminative features are applied to an artificial neural network for classification of skin lesions as either melanoma

or benign. Experimental results demonstrate that our proposed system outperforms comparable state-of-the-art methods in terms of classification accuracy.

The rest of this paper is organized as follow. In Section 2 our proposed method for automatic classification of skin lesion images is described in details. The experimental results are presented in Section 3, and Section 4 concludes the paper.

2. PROPOSED METHOD

In this section the proposed method is explained. In order to determine whether the lesion is malignant or benign, the following steps are applied on the input image of skin surface:

(1) Illumination correction and lesion segmentation: firstly some preprocessing is done in order to increase segmentation accuracy. Since the images are gathered with consumer level digital cameras, usually some noise and illumination effects exist that should be properly handled. The input images contain both healthy and pigmented regions; hence for effective feature extraction the lesion areas (regions of interest) should be segmented.

(2) Color feature extraction: afterward, 10 features, namely f_1 to f_{10}, are extracted based on color characteristics of pigmented and healthy parts of skin. This is based on dermatological color aspects of melanoma. The proposed features are designed to be discriminative based on specific properties of cancerous and benign cells.

(3) Classification: finally the extracted 10 dimensional feature vector is fed into an artificial neural network for automatic diagnosis and classification of the suspicious mole.

Our proposed automatic diagnosis system is summarized in Fig. 1. In the rest of this section the above mentioned steps are described in details.

2.1. Illumination Correction and Lesion Segmentation

This step is similar to [12], except we perform some post-processing to better the performance of the segmentation stage.

Since the photographs are taken by users with ordinary cameras, usually some reflections from the skin surface happen which can impact all of the following steps. Illumination effects appear as rapid changes in the saturation and value channels of the HSV color space. These effects can be eliminated by smoothing out sharp gradient values in these channels. Furthermore, additional noisy artifacts are removed using the edge preserving smoothing filters as are proposed in [12] and [15].

After this pre-processing step, segmentation is done in the HSV color space. This is done by a k-means clustering in a 3 dimensional space while treating the H dimension as an angle [12]. This clustering segments the image pixels into 2 groups of skin and lesion regions. Quality of the segmentation mask is further improved by some morphological operations of closing, opening, and hole-filling. Finally, the biggest connected component in the segmentation map is selected as a lesion region mask.

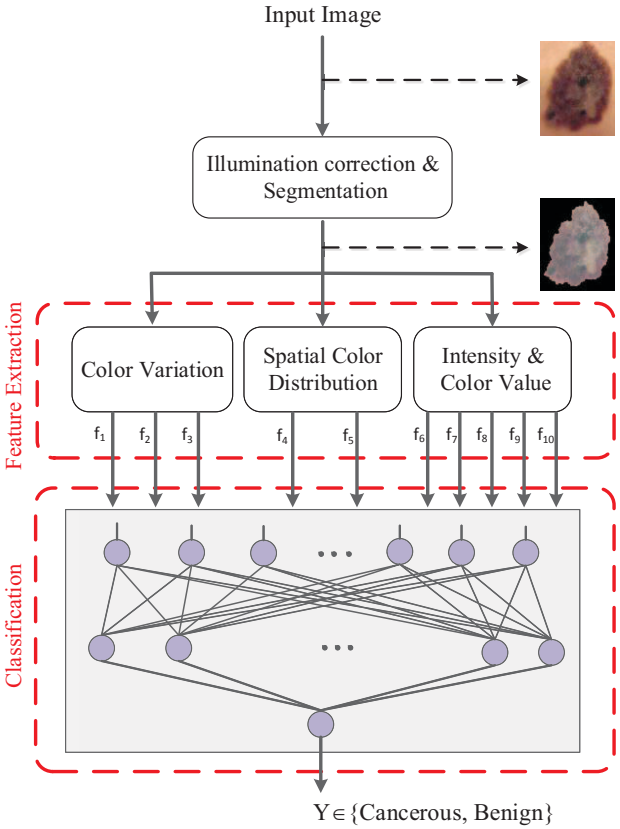


Fig.1. Block diagram of the proposed method.

2.2. Color Features Extraction

One of the most widely used methods for scoring suspicious lesions for malignancy is the ABCD rule of dermatology. In this paper the focus is on color analysis of pigmented lesion and the results will be compared to similar approaches in the literature regarding color along with other dermatological descriptors.

After automatic lesion segmentation done in the previous step, some melanoma features are proposed to be extracted based on region masks. We take advantage of 5 proposed high level descriptor features along with 5 conventional color features. The proposed set of features (f_1 to f_{10}) are intended to describe three dermatological color characteristics that are discriminative between malignant and benign lesions. These aspects are as follows:

- Color Variation (f_1, f_2, f_3)
- Spatial Color Distribution (f_4, f_5)
- Intensity and Color Value ($f_6, f_7, f_8, f_9, f_{10}$)

One of the main alerting signs of melanoma is the presence of multiple colors. Dermatologists characterize the coloring of lesions as a mixture of 1) red, 2) blue-gray, 3) white, 4) dark brown, 5) light brown, and 6) black. Hence, a lesion could have a number of colors. There is a direct

relation between the number of colors in a lesion and the risk of melanoma [16]. For evaluation of color variation in a segmented region, a Fuzzy C-Means (FCM) clustering is performed based on 3 dimensional RGB values of pixels in that region. Prior to that, noisy values are reduced by applying a Gaussian filter with $\sigma = 15$.

FCM is an unsupervised fuzzy classifier [17] which aims to group data into predefined number of clusters. Each data element has a fuzzy membership to each group based on its similarity to cluster centroid. Suppose $X = (x_1, x_2, \dots, x_n)$ to be an n input data in a d dimensional space. The objective of FCM is to find a set of c clusters as $C = (C_1, C_2, \dots, C_c)$ that minimize objective function J as [17]:

$$J = \sum_{i=1}^{n}\sum_{j=1}^{c} u_{ij}^{m}\|x_i - c_j\|^2, \quad (1)$$

where c_j is the center of j^{th} cluster and u is calculated by:

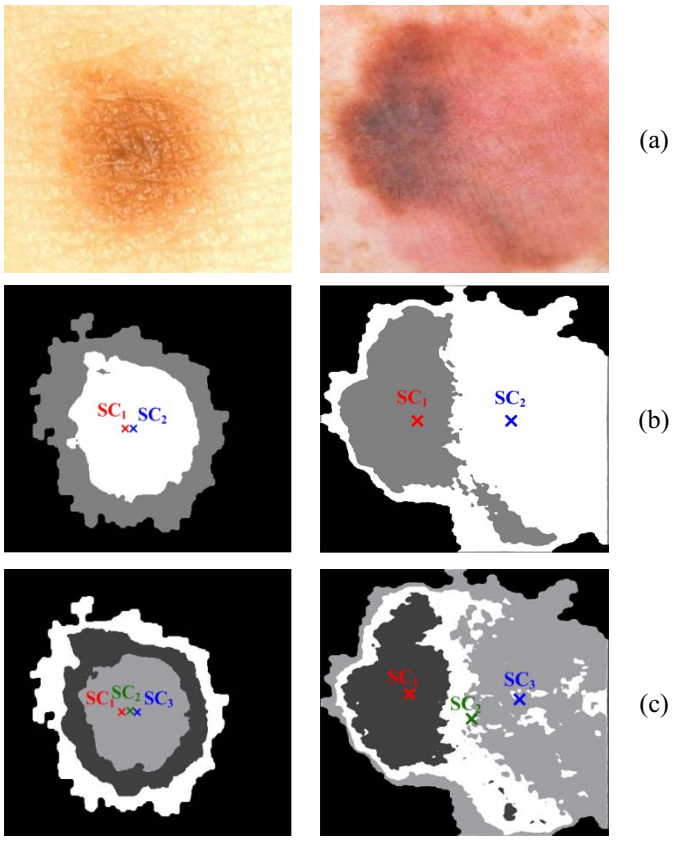
$$u_{ij}^{m} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}} \quad (2)$$

where m adjusts the fuzziness of clustering ($m = 2$) and $||^2$ denotes squared distance in a d dimensional space . The FCM objective function can be minimized by iteratively using the center update equations as shown by [17].

To measure color variations, values of pixels in the lesion region are considered as the input for the FCM classifier. In the 3 dimensional color space the sum of absolute difference between calculated centers of clusters can be used as a measure that describes the variety of colors in the segmented lesion. In this paper, FCM is performed for 2 and 3 number of centers ($c = 2, c = 3$). The difference between center values is used as the first two features of $f_1$and f_2. Moreover the sum of absolute difference between center values in $c = 2$ and $c = 3$ is used as another feature addressing the color variation ($f_3 = |f_1 - f_2|$). Hence, these three absolute differences are considered as our first three features. In case of non-melanoma lesions, homogeneity of colors usually exists and there is little difference between cluster centers. This is contrary to multicolor melanoma lesions.

Along with the existing of different colors, spatial distribution of the colors is of importance for diagnostic purposes. In some cases non-cancerous lesions may also compose of more than one single color, but the key point is that their color variations are relatively smooth, e.g. dark in the center of lesion and light at the surroundings [16]. In our proposed feature set, f_4 and f_5 are targeted to evaluate the spatial distribution of the colors. To this end we notice location of spatial centroid (SC) of clusters, which is a point in the (x, y) coordinates, defined as follows for i^{th} cluster:

$$\begin{aligned}&\big(SC_i(x), SC_i(y)\big)\\ &= \Big(mean\big(p(x)\big), mean\big(p(y)\big)\Big) : p \epsilon C_i,\end{aligned} \quad (3)$$



(a) (b) (c)

Fig. 2. A sample image of benign (left column) and melanoma (right column) from dataset, (a) input image, (b) clustered lesion with $c = 2$ (c) clustered lesion with $c = 3$ (Spatial Centroid (SC) of clusters is shown by an '×' sign).

where p is a point in cluster C_i. Even when there are more than one color in the lesion, if the changes in the colors are from the center of the lesion towards the border of the lesion then the lesion is most likely benign. On the other hand, it is common in melanoma cases to have separated color regions. We can describe this characteristic by taking advantage of the SC locations, so spatial color distribution (SCD) of a lesion is defined as:

$$SCD(c) = \sum_{i=1}^{c}\sum_{j=i+1}^{c}\|SC_i - SC_j\|, \quad (4)$$

where $||$ is distance between 2 points as sum of absolute difference in x and y dimensions. This distance value is normalized by dividing it by lesion's width and height. We used $SCD(c)$ with $c = 2,\ c = 3$ as our 4^{th} and 5^{th} features. In Fig. 2, we are showing the location of SCs for the sample images. Usually in melanoma cases the distance between spatial centroids is high, while in benign moles the SCs are close to each other. This suggests when irregularity of color distribution is high in a lesion the probability of melanoma is high too.

Since melanoma cases usually have specific range of intensity values we also use some conventional features regarding the intensity values of a lesion. To describe this

property some common histogram-based features (mean, variance, skewness and kurtosis) are derived from the histogram of the V component in the HSV color space. These features represent intensity and color distribution in pigmented regions. Finally the mean difference, in the RGB color space, between the healthy skin and the lesion area is considered as f_{10} in our 10 dimensional feature vector.

In the next step the extracted set of features is used to classify input image as malignant or benign lesions. The used classifier is described in following.

2.3. Classification

Experience-based learning is the main aspect of common classifiers like artificial neural networks (ANN), which makes them applicable for diagnostic issues. ANNs are powerful tools inspired by biological human neural network. These structures have been used as pattern classifiers in many recognition and classification applications such as various medical diagnosis problems [18]. Here by using robust and effective color related features, which were described in the previous subsection, the neural network learns and gains experience about mapping of a set of symptoms into a set of possible diagnostic classes, i.e. malignant melanoma and benign moles.

Configuration and implementation details of the used neural network are discussed in the next section.

3. EXPERIMENTS

The performance of our proposed system is evaluated on a dataset of non-dermoscopic images, publicly available in [19]. This dataset consists of 70 melanoma and 100 benign images from the digital Image archive of the Department of Dermatology of the University Medical Center Groningen (UMCG). These images are captured by digital cameras and they are different from dermoscopic images which contain more detailed information. Dermoscopic images are also subject to less illumination and noise effects. The neural network which is used in the classification stage, is a two layer feed forward neural network. This network has a tan-sigmoid transfer function in its hidden layer and it has linear transfer function in the output layer. The number of neurons in the hidden layer is set by trial and error to 15. To avoid overtraining of the network, resilient back-propagation is used as the training function.

In order to evaluate the classification results of the proposed method, we randomly split the dataset into train and test sets with three quarters of images used for training and one quarter used for test purposes. This means 125 images are used as the training data (50 melanoma, 75 benign) and 45 images for the test (20 melanoma, 25 benign). There is no overlap between the chosen training data and those that are selected for the test. To make sure that the results are independent from selected images for training or test, the classification process was repeated 1000 times and the mean of obtained results is reported as the final result. For quantitative evaluation of our method, we use 5 metrics which are commonly used in classification problems. These metrics are namely PPV (positive predicted value), NPV (negative predicted value), sensitivity, specificity, and accuracy.

In Table 1 we compare our classification results with MED-NODE [12]. This is the most recent method in the literature and which also has used the same dataset as we did. It has proposed a 12 dimensional feature vector as its color descriptor. In order to have a fair comparison with MED-NODE only results of applying color descriptors in that method are reported here. The proposed method is also compared with SpotMole [13], using the same dataset as the evaluation set. It is one of the newest and most successful web applications in this area according to the user and press reviews [12]. It is worth mentioning that SpotMole takes advantage of all ABCD descriptors in order to classify images. However, our proposed method by use of only color related features still outperforms SpotMole in four of the five classification metrics. This superior achievement is mainly the result of extraction of effective and discriminative features. It should also be noted that high sensitivity for a cancer diagnostic algorithm is of higher importance than specificity of the method. Considering this we see that our algorithm outperforms the other two state of the art methods.

Table 1. Quantitative comparison of diagnostic results with competing algorithms. Best results are bolded.

Method	MED-NODE [12] (Color Features)	SpotMole [13] (All Features)	Proposed
Sensitivity	0.74	**0.82**	**0.82**
Specificity	**0.72**	0.57	0.71
PPV	0.64	0.56	**0.67**
NPV	0.81	0.83	**0.85**
Accuracy	0.73	0.67	**0.76**

4. CONCLUSION

In this paper a set of effective color features regarding specific melanoma characteristics is used for classification of non-dermoscopic skin images. An image of a skin lesion, by a standard camera, may be subject to noise and illumination effects and usually contains less information as compare to a dermoscopic image. But conventional images are easily available. FCM clustering of lesion's color can be used for a measurement of color variation and distribution. We showed that such features, along with other conventional color and intensity features are effective means of melanoma detection. Experimental results show high sensitivity of our algorithm which means it can detect cancerous lesions better than comparable algorithms. Our specificity was 71% while another method was 72%, which means the other method has marked slightly more non-cancer cases as benign lesions. We also outperformed other methods in terms of PPV, NPV, and accuracy.

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