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TRE Technique Based Dermoscopic Image Segmentation of Skin Lesions for Skin Cancer

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Abstract
Melanoma is the deadliest form of skin cancer. Incidence rates of melanoma have been increasing, especially among non-Hispanic white males and females, but survival rates are high if detected early. Due to the costs for dermatologists to screen every patient, there is a need for an automated system to assess a patient's risk of melanoma using images of their skin lesions captured using a standard digital camera. One challenge in implementing such a system is locating the skin lesion in the digital image. A novel texture-based skin lesion segmentation algorithm is proposed. A set of representative texture distributions are learned from an illumination-corrected photograph and texture distinctiveness metric is calculated for each distribution. Next, regions in the image are classified as normal skin or lesion based on the occurrence of representative texture distributions. The proposed segmentation framework is tested by comparing lesion segmentation results and melanoma classification results to results using other state-of-art algorithms. The proposed framework has higher segmentation accuracy compared to all other tested algorithms.

Index Terms*—Feature extraction, melanoma, color spaces, image segmentation, level set method, medical imaging.*

I. Introduction

The most dangerous form of skin cancer, these cancerous growths develop when unrepaired DNA damage to skin cells (most often caused by ultraviolet radiation from sunshine or tanning beds) triggers mutations (genetic defects) that lead the skin cells to multiply rapidly and form malignant tumors. These tumors originate in the pigment-producing melanocytes in the basallayer of the epidermis. Melanomas often resemble moles; some develop from moles. The majority of melanomas are black or brown, but they can also be skin-colored, pink, red, purple, blue or white. Melanoma is caused mainly by intense, occasional UV exposure (frequently leading to sunburn), especially in those who are genetically predisposed to the disease. Melanoma kills an estimated 9,940 people in the world annually [1].Initial melanoma detection is usually done visually by a general practitioner, followed by a follow-up appointment with a dermatologist for further visual inspection. This process is time- and cost-inefficient, especially with increasing incidence rates [2]. Additionally, the two factors make it difficult to visually identify melanoma that is Melanoma can be very similar in appearance to benign nevi (i.e., noncancerous "moles") at the surface during it's early to mid stages and Melanoma can take on widely varying shapes and forms.

Dermatologists commonly use metrics such as the ABCD (asymmetry, border irregularity, color patterns, and diameter) criteria [3], [4] or the seven-point checklist [5]. However, usage of these metrics is very subjective, leading to large into observe variability [6]. Systematic objective decision support systems can help meet the demand of the rising rate of melanoma and help reduce subjectivity. The remainder of this paper is organized as follows. Section II present a related works with skin lesion segmentation and melanoma detection, Section III provides a framework for designing Intuitive Features. Section IV presents a set of feature models of the ABCD melanoma criteria. Section V presents statistical analyses of the proposed TRE features as well as experimental segmentation results of the Intuitive Features using the public databases Dermatology Information System [7] and DermQuest [8]. Results and conclusions are drawn in Section VI.

II. Related Works

The separation of image content into semantic parts plays a vital role in applications such as compression, enhancement, restoration, and more. In recent years, several pioneering works suggested such a separation be based on variational formulation and others using independent component analysis and sparsity. In [1]J.-L. Starck; M. Elad presents a novel method for separating images into texture and piecewise smooth (cartoon) parts, exploiting both the variational and the sparsity mechanisms. The method combines the basis pursuit denoising (BPDN) algorithm and the total-variation (TV) regularization scheme. The basic idea presented in this paper is the use of twoappropriate dictionaries, one for the representation of textures and the other for the natural scene parts assumed to be piecewise smooth. Both dictionaries are chosen such that they lead to sparse representations over one type of image-content (either texture or piecewise smooth).

Multiscale segmentation is an essential step for higher 1level image processing in remote sensing. This paper presents a new multiscale SRMMHR segmentation method integrating the advantages of Statistical Region Merging (SRM) for initial segmentation and the Minimum Heterogeneity Rule (MHR) for object merging. The high-resolution (HR) Quick Bird imageries are used to demonstrate the SRMMHR segmentation method. In [4] Haitao Li; HaiyanGu presents SRM segmentation method not only considers spectral, shape, and scale information, but also has the ability to cope with significant noise corruption and handle occlusions. The MHR used for merging objects takes advantage of its spectral, shape, scale information, and the local and global information. Compared with the Fractal Net Evolution Approach (FNEA) that Cognition adopted and SRM methods, the results show that the proposed method wipes off small redundant objects existed in traditional SRM methods, avoids the phenomena where the big homogeneity region has lots of small similar regions existed in the FNEA method, and gets more integrated and accurate objects. Therefore, the proposed SRMMHR segmentation method is an efficient multiscale segmentation method for HR imagery.

The main contribution we propose a segmentation algorithm based on texture distinctiveness (TD) to locate skin lesions in photographs. This algorithm is referred to as the TD lesion segmentation (TDS) algorithm. The main contributions are the introduction of a joint statistical TD metric and a texture-based region classification algorithm. TD captures the dissimilarity between learned representative texture distributions. Our proposed sparse texture model algorithm incorporates statistical information. We introduce the use of joint statistical information to characterize skin and lesion textures as representative texture distributions. The advantage of using a joint probabilistic sparse model is that the sparse texture distributions can model both local and global texture characteristics.

III.THRESHOLD REGION EDGING (TRE)

A feature extraction framework for intuitive classification advantages of designing Intuitive features are discussed followed by general instructions for designing an Intuitive features. This framework is used in Section III for extracting features relevant to skin cancer detection. A mathematical model that has been carefully designed to describe some human-observable characteristic, and whose outcome can be intuited in a natural (e.g., visual) way. In contrast to TRE usually require more upfront design time. An intuitive feature captures a specific characteristic that is relevant to the given application (e.g., complexity of the color distribution, smoothness of an object), making intuitive feedback possible.

The first step in designing an intuitive feature is to study the target user. The goal is to understand how they analyze the data. Recall that intuitive feature is modeled according to a human-observable characteristic. The second step is to identify available tools for modeling high-level characteristics. For example, perceptually uniform color spaces (e.g., CIE L*a*b*) can be used to quantify color distribution patterns. The third step is the modeling stage. The feature should describe a high-level characteristic such that intuitive feedback can be provided to the user (e.g., graphically).

IV. FEATURE MODELS OF THE ABCD MELANOMA CRITERIA

These features were designed to model the intuitive ABCD metric widely used by dermatologists. Since the feature models follow the HLIF framework, the system can provide intuitive diagnostic rationale. The proposed asymmetry features are extensions of the work presented in [15], and the border irregularity features are extensions of the work presented in [16], [17]. The diameter (“D”) criterion was not addressed since the acquisition process was unconstrained, making scale inference challenging.

A. Asymmetry

Dermatologists try to identify asymmetry of the shape and/or color of a skin lesion. While benign nevi tend to have homogeneous color distributions, melanomas tend to be asymmetrically pigmented. Furthermore, while benign nevi tend to be elliptically shaped, melanomas tend to have complex shapes.

The goal of a TRE for describing color asymmetry is to differentiate lesionsbased on the spatial uniformity and symmetry of the color distribution. This feature is similar to field color asymmetry; except that Earth mover’s distance (EMD) is used instead of entropy and many axes of separation are considered.

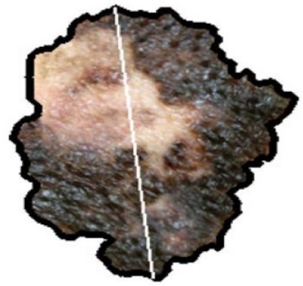


Fig. 1 Asymmetry Criteria

A lesion's shape becomes less likely to be symmetric as it deviates from the ideal elliptical structure. Structural asymmetry can, therefore, be approximated by the coarse complexity of the lesion's spatial structure. The lesion's shape was reconstructed using Fourier descriptors in two coarse manners to quantify structure complexity, according to the following algorithm. This builds on previous features using Fourier descriptors

Given a segmented skin lesion, the major axis was chosen as the initial axis of separation (AoS). The major axis passes through the center of mass (i.e., centroid) of the lesion shape and describes the maximum amount of structural variation (i.e., the transverse diameter of the fitted ellipse). The color distributions in the perceptually uniform CIE L*a*b* space on each side of this AoS were compared. In particular, k "signatures" on both sides of the AoS were determined using k-means clustering, using the final k clusters as color signatures. Mathematically

S^{θ}_{i} = k-means (C^{θ}_{i}, k)

The final feature calculation is as follows:

$f^{A}_{1} = \max_{\theta}\{EMD\ (S^{\theta}_{1}, S^{\theta}_{2})$

B. Border Irregularity

Dermatologists try to identify irregular borders of the skin lesion. Melanoma cases tend to have highly irregular pigmented borders such as "spiky" borders.

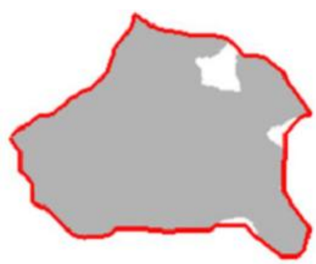


Fig. 2 Border Criteria

Melanoma cases often contain abrupt localized pigmentation patterns, such as "spikes." In order to quantify these "fine" irregularities, the theory of morphological operations can be used. This feature draws from the morphological shape representationtheory. Morphological operations, unlike Fourier descriptors, are able to manipulate shapes on a local scale. The amount of localized abrupt pigmentation can be measured using morphological opening and closing. The resultant normalized difference in area from these operations was compared to the original lesion. Abrupt pigmentation can be measured using morphological opening and closing. The resultant normalized difference in area from these operations was compared to the original lesion.This can be measured using the normalized self-dual top-hat operator, described in the following.

Fig. 3 Color Criteria (Color complexity analysis and Reconstruction)

The final feature calculation is as follows: $f_1^B = (T_b + T_w)/A_{lesion}$

C. Color

Recurring color patterns have emerged in melanoma cases. Unfortunately, most of the ABCD color characteristics are only observable with the aid of a dermatoscope. Furthermore, many image processing tools for medical image analysis were developed for monochrome images. Many existing color features are statistical features in either RGB or alternative color spaces. There is, therefore, a significant demand for novel research on quantifying color information pertaining to melanoma detection, particularly using standard camera images.

First a color complexity analysis used to design the proceeding TRE. The color complexity analysis framework is comprised of the following four steps.

- **Step 1** : Transform the image to a perceptually uniform color space.
- **Step 2** : Construct color-spatial representations that model the color information for a patch (i.e., local grid) of pixels.
- **Step 3** : Cluster the patch representations into k color clusters.
- **Step 4** : Quantify the variance found using the original lesion and the k representative colors.

D. Diameter

Benign moles usually have a smaller diameter than malignant ones. Melanomas usually are larger in diameter than the eraser on your pencil tip (¼ inch or 6mm), but they may sometimes be smaller when firstdetected. The size of the mole is greater than 1/4 inch (6 mm), about the size of a pencil eraser. Any growth of a mole should be evaluated.There is another criteria and not mentioned in this paper called Evolution. There is a change in the size, shape, symptoms, surface or color of a mole.

V. EXPREMENTAL RESULTS

This section presents the experimental evaluation of the TRE proposed in Section III. This feature set was analysed with a state-of-the-art LLF set modeled according to the ABCD rule [11], which is a complete ABCD feature set that was shown to attain higher accuracy than existing full ABCD feature sets [11]. The final proposed feature set was the combined set of TRE. Finally, observations and limitations of the experimental results are discussed.

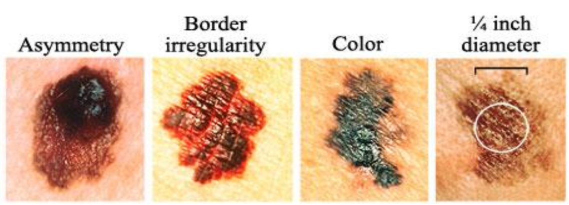


Fig. 4 Diameter and ABCD's Criteria of Skin Cancer Features examples

A. Data

We collected 206 images of skin lesion, which were obtained using standard consumer-grade cameras in varying and unconstrained environmental conditions. These images were Extracted from the online public databases Dermatology Information System [7] and DermQuest [8]. Of these images, 119 are melanomas, and 87 are not melanoma. Each image contains a single lesion of interest. This is the same dataset used in [15].

B. Experimental Setup

For each image, the lesion was manually segmented to provide an "ideal" segmentation for feature extraction. That is, we wished to analyze the feature extraction performance irrespective of an automatic segmentation's accuracy. We rendered the images rotation- and scale-invariant by performing the following preprocessing step: prior to feature extraction, the image was rotated so that the lesion's major axis was parallel to the horizontal axis, and the lesion fit within a 200 × 200 bounding box while maintaining the original aspect ratio. The decision support workflow was implemented in MATLAB.

1) Preprocessing
2) Feature Extraction
3) Classification (ABCD Criteria)
4) Output

One would expect that a doctor is more likely to trust a computer-generated malignancy prediction if intuitive rationale is provided along with the predicted label.

Each HLIF was designed according to the ABCD criteria, which is a visual metric commonly used by dermatologists. To infer intuitive rationale is simple, as each HLIF represents information for which the dermatologist themself would look.

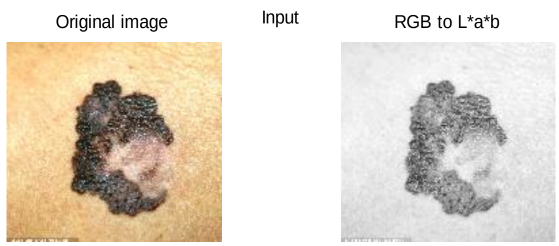
This information can usually be relayed graphically to the user, since melanoma detection is a very visual process.

C. Results

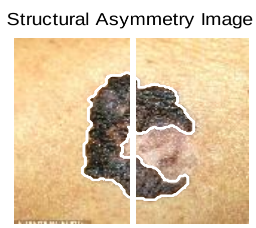
Example intuitive visualization for the case presented in below Figures. Upon analyzing the image, the interface indicates that there is apparent color asymmetry and complex color patterns by highlighting the relevant ABCD terms.

The features had been normalized on the training data so that the significance of a feature calculation could be easily interpreted by the number of standard deviations from the sample mean feature score.

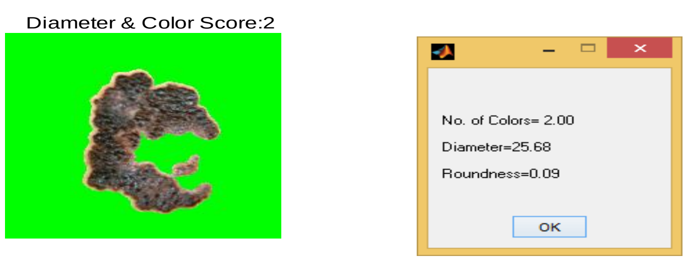
1.Input Image and Pre-processing L*a*b* color space



2. Asymmetry Image



5. Diameter Interface



A large hindrance of the current state of skin cancer detection research is the limited amount of data available to the scientific community [18]. Dermatologists may take pictures of skin lesions, but restrict them to within their clinic, due perhaps to either privacy or commercialization concerns. In order to ensure robust models and statistical validity, much larger datasets must be accumulated for training and testing these decision support systems

VI. CONCLUSION

In summary, a novel lesion segmentation algorithm using the concept of TD is proposed. A probabilistic TD metric is introduced based on a learned model of normal skin and lesion textures. Representative texture distributions are learned from the image itself and the TD metric captures the dissimilarity between pairs of texture distributions. Then, the image is divided into numerous smaller regions and each of those regions is segment as lesion or skin based on the TD map. The entire proposed framework is tested by using the illumination corrected images as the input to the texture-based segmentation algorithm. It is compared to state-of-art lesion segmentation algorithms, including three algorithms designed for lesion images. The proposed framework produces the highest segmentation accuracy using manually segmented images as ground truth. A larger data collection and annotation process, including additional testing on a wide range of images, will be undertaken as future work. While the experimental results show that the proposed method is able to segment the lesion in images of different scales and levels of quality, it is worth conducting a more comprehensive analysis on the impact of image quality and scale on the proposed method.

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