ISSN (ONLINE): 2395-695X
ISSN (PRINT): 2395-695X
Available online at www.ijarbest.com
International Journal of Advanced Research in Biology, Engineering, Science and Technology (IJARBEST)
Vol. 2, Issue 1, January 2016

Skin Lesions Description from Digital Images Using Intuitive Feature Extraction

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***Abstract*— A set of high-level intuitive features (HLIFs) is proposed to quantitatively describe melanoma in standard camera images. Melanoma is the deadliest form of skin cancer. With rising incidence rates and subjectivity in current clinical detection methods, there is a need for melanoma decision support systems. The proposed HLIFs were designed to model the ABCD criteria commonly used by dermatologists such that each HLIF represents a human-observable characteristic. As such, intuitive diagnostic rationale can be conveyed to the user. The result of HLIF having much longer point of ABCD to decrease the all over competency to implement the feature extraction in lesion skin image.**

***Index Terms*— Feature extraction, melanoma, image segmentation, 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 basal layer 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 Intuitive Features as well as experimental classification 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

Dermatoscopes are optical devices that manipulate light characteristics to elucidate subsurface information. Reviews of existing features can be found in [9] and [10]. Unfortunately, the clinical use of Dermatoscopes is limited, therefore, turned to analyzing images obtained with standard consumer-grade cameras.

Some feature sets have been proposed for images obtained with standard cameras (e.g., [11]); however, these feature sets combined many low-level features (LLFs) to try to approximate ABCD. The importance of high-level over low-level features has been recently discussed [12]. LLFs are (usually simple) features that were not designed to model a high-level characteristic (e.g., asymmetry). This limits the system's ability to present diagnostic rationale, which is important for user-system trust [13]. System credibility has received attention in human computer interaction research [14]; however, these ideas have not been explicitly introduced to melanoma decision support system research.

The main contribution of this study is a set of high-level intuitive features (HLIFs) for analyzing skin lesions. Intuitive features are designed explicitly to model human-observable characteristics. As such, an Intuitive features design is usually more complex than that of an LLF. A decision support system that extracts Intuitive features can provide intuitive diagnostic rationale to the user according to what they would expect to observe, with the aim of increasing user-system trust. Experimental results show that concatenating a small set of Intuitive features and a set of LLFs increased classification accuracy over the LLF alone. This study builds on previous work [15] by extending the previously proposed asymmetry and border irregularity Intuitive features, and by proposing new HLIFs for color variation.

III. INTUITIVE FEATURE EXTRACTION

A feature extraction framework for intuitive classification advantages of designing Intuitive features are discussed

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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 LLFs, HLIFs 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 HLIFs

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 an HLIF for describing color asymmetry is to differentiate lesions based 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.

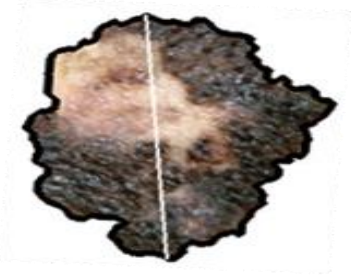

Fig. 1 Asymmetry Criteria

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

$$S^{\theta}_{i} = k\text{-}means\ (C^{\theta}_{i}, k)$$

The final feature calculation is as follows:

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

B. Border Irregularity HLIFs

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

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 representation theory. Morphological operations, unlike Fourier descriptors, are able to manipulate shapes on a local scale.

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Fig. 2 Border Criteria

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. This can be measured using the normalized self-dual top-hat operator, described in the following.

The final feature calculation is as follows:

$$f_1^B = (T_b + T_w)/A_{lesion}$$

C. Color HLIFs

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.

Fig. 3 Color Criteria (Color complexity analysis

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 framework is presented, which was used to design the proceeding HLIFs. 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 HLIFs

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 first detected. 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 (such asitching or tenderness), surface (especially bleeding), or color of a mole.

V. Experimental Results

This section presents the experimental evaluation of the HLIFs 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 HLIFs and LLFs. Finally, observations and limitations of the experimental results are discussed.

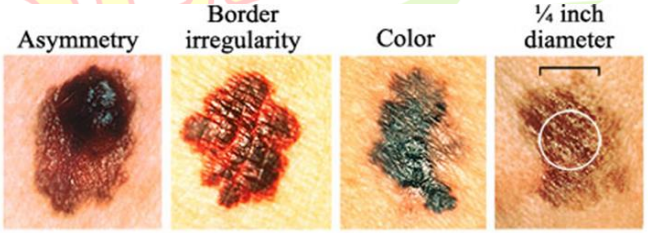

Fig. 4 Diameter and ABCD's Criteria of Skin Cancer Features examples

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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.

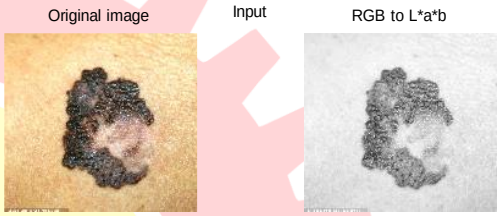
C. Results

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 tems.

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.

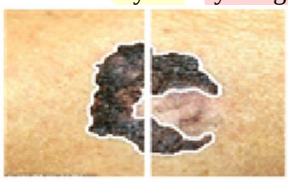
The below figures provides an example interface for intuitive visualization of the color asymmetry, border, color and diameter.

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



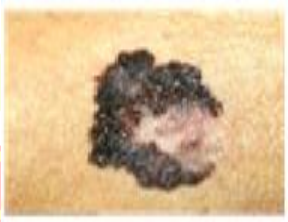
2. Asymmetry Image

Structural asymmetry image

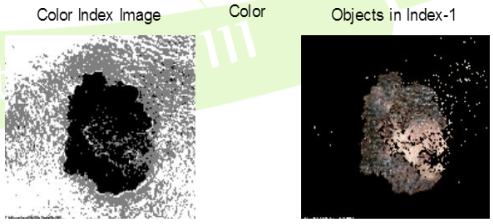


3. Border Image

Skin border image



4. Color Image



5. Diameter Interface

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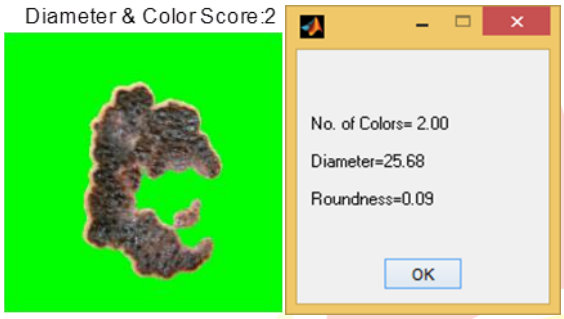

A large hindrance of the current state of skin cancer detection research is the limited amount of data available to the scientific community [18]. Dermatologists may take pictures of skin lesions, but restrict them to within their clinic, due perhaps to either privacy or commercialization concerns. In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

This is especially the case since the images are obtained in unconstrained environments, leading to extremely large variations in acquired data.

VI. Conclusion And Future Work

This paper has presented a framework for designing HLIFs, and has proposed a full set of HLIFs for quantifying skin lesion characteristics for melanoma detection. HLIFs are feature calculations that have been meticulously deled to describe some human-observable characteristic, and from which rationale can be relayed to the user in some intuitive (perhaps visual) manner. It was shown in that skin lesion classification accuracy was improved when concatenating a small set of HLIFs and a state-of-the-art LLF set. Individual HLIFs were shown to have more statistical significance with respect to separating the data than individual LLFs.

In Future, a novel lesion segmentation algorithm using the concept of complete TD will propose in future. 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. 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 future work.

References

[1] American Cancer Society, "*Cancer Facts & Figures 2011*," American Cancer Society, Atlanta, GA, USA, Tech. Rep. ACSPC-029771, 2011.

[2] W. Stolz, A. Riemann, A. Cognetta, L. Pillet, W. Abmayr, D. Holzel, P. Bilek, F. Nachbar, M. Landthaler, and O. Braun-Falco, "*ABCD rule of dermatoscopy: A new practical method for early recognition of malignant melanoma*," Eur. J. Dermatol., vol. 4, no. 7, pp. 521–527, 1994.

[3] F. Nachbar, W. Stolz, T. Merkle, A. B. Cognetta, T. Vogt, M. Landthaler, P. Bilek, O. Braun-Falco, and G. Plewig, "*The ABCD rule of dermatoscopy: High prospective value in the diagnosis of doubtful melanocytic skin lesions*," J. Amer. Academy Dermatol., vol. 30, no. 4, pp. 551–559, 1994.

[4] G. Argenziano, G. Fabbrocini, P. Carli, V. De Giorgi, E. Sammarco, and M. Delfino, "*Epiluminescence microscopy for the diagnosis of doubtful melanocytic skin lesions: Comparison of the abcd rule of dermatoscopy and a new 7-point checklist based on pattern analysis*," Archives Dermatol., vol. 134, no. 12, pp. 1563–1570, 1998.

[5] Y. Wazaefi, A. Tenenhaus, A. Nkengne, J.-F. Horn, A. Giron, S. Paris, and B. Fertil, "*The impact of the observation of predictive features on the diagnosis of pigmented skin lesions and the therapeutic decision,"* presented at the Int. Conf. on Data Mining, Las Vegas, Nevada, USA, 2012.

[6] K. Korotkov and R. Garcia, "*Computerized analysis of pigmented skin lesions: A review*," Artif. Intell. Med., vol. 56, no. 2, pp. 69–90, 2012.

[7] I. Maglogiannis and C. N. Doukas, *"Overview of advanced computer vision systems for skin lesions characterization*," IEEE Trans. Inf. Technol. Biomed., vol. 13, no. 5, pp. 721–733, Sep. 2009.

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International Journal of Advanced Research in Biology, Engineering, Science and Technology (IJARBEST)
Vol. 2, Issue 1, January 2016

[8] P. G. Cavalcanti and J. Scharcanski, "Automated prescreening of pigmented skin lesions using standard cameras," Comput. Med. Imag. Graph., vol. 35, no. 6, pp. 481–491, 2011.

[9] M. E. Celebi, H. A. Kingravi, B. Uddin, H. Iyatomi, Y. A. Aslandogan, W. V. Stoecker, and R. H. Moss, "*A methodological approach to the classification of dermoscopy images*," Comput. Med. Imag. Graph., vol. 31, no. 6, pp. 362–373, 2007.

[10] B. M. Muir, "*Trust between humans and machines, and the design of decision aids*," Int. J. Man-Mach. Stud., vol. 27, pp. 527–539, 1987.

[11] B. J. Fogg, "*Persuasive technology: using computers to change what we think and do*," Ubiquity, vol. 2002, art. no. 5, Dec. 2002.

[12] R. Amelard, A. Wong, and D. A. Clausi, "*Extracting high-level intuitive features (HLIF) for classifying skin lesions using standard camera images*," in Proc. Conf. Comput. Robot Vis., Toronto, Canada, May 2012, pp. 396–403.

[13] R. Amelard, A. Wong, and D. A. Clausi, "*Extracting morphological highlevel intuitive features (HLIF) for enhancing skin lesion classification*," in Proc. Ann. Int. Conf. IEEE Eng. Med. Biol. Soc., San Diego, CA, USA, Sep. 28, 2012–Sep. 1, 2012, pp. 4458–4461.

[14] R. Amelard, J. Glaister, A. Wong, and D. A. Clausi, "*Melanoma decision support using lighting-corrected intuitive feature models*," in Computer Vision Techniques for the Diagnosis of Skin Cancer (Series in BioEngineering), J. Scharcanski and M. E. Celebi, Eds. New York, NY, USA: Springer, 2013

[15] G. R. Day and R. H. Barbour, "*Automated melanoma diagnosis: Where are we at?*" Skin Res. Technol., vol. 6, no. 1, pp. 1–5, 2000.

[16] N. Howlader, A. Noone, M. Krapcho, J. Garshell, N. Neyman, S. Altekruse, C. Kosary, M. Yu, J. Ruhl, Z. Tatalovich, H. Cho, A. Mariotto, D. Lewis, H. Chen, E. Feuer, and K. Cronin. (2012, Apr.). "SEER cancer statistics review, 1975-2010," National Cancer Institute, Bethesda, MD, USA, [Online]. Available: http://seer.cancer.gov/ archive/csr/1975_2010/citation

[17] Dermatology Information System. (2012). [Online]. Available: http://www.dermis.net

[18] DermQuest. (2012). [Online]. Available: http://www.dermquest.com