Early Diagnosis and Predictive Monitoring of Skin Diseases

Nikhil J. Dhinagar, *IEEE EMBS Student Member*, and Mehmet Celenk, *IEEE Member*

***Abstract*—Skin diseases like melanoma are traditionally screened by a visual analysis of key features, such as the pigmentation and vascularity of the region of interest. Monitoring the changes of these features during follow-up imaging sessions is critical towards a correct medical diagnosis. This paper proposes a framework to monitor these changes on the skin over time. The proposed framework utilizes the Lucas-Kanade displacement flow implementation to detect the severity of spatial changes in the skin. These spatial changes are captured via the magnitude and direction of the vectors in the resultant displacement field. This change monitoring is tested for surface and sub-surface skin image data. The proposed framework is developed and validated with skin samples of cutaneous melanoma, setting the stage for future extension to images from other skin diseases. The skin sample images would be classified as high and low risk based on the severity of change. Further, a predictive algorithm is devised to estimate the change in the high risk skin lesions, providing significant information to determine the course of medical action.**

I. Introduction

The average annual number of adults treated for any skin cancer in the US (non-melanoma skin cancer and melanoma) increased from 3.4 to 4.9 million between 2002-2006 and 2007-2011 with the largest proportion representing keratinocytic tumors, while the average number treated for all other cancers increased from 7.8 to 10.3 million [1]. Cutaneous melanoma and non-melanoma skin cancers are initially diagnosed based on visual attributes of a lesion or mole. Cutaneous melanocytic lesions metastasize aggressively and the tumor thickness becomes a critically important prognostic factor. The visual examination of such suspicious lesions leads to a clinical biopsy of the affected skin and the cross-section of the skin tissue is examined by pathological assessment. However, this diagnostic process is time-consuming, invasive and subjective to medical experience.

A. Background

In recent times, with vast improvement in imaging optics, imaging and smart phone technology and different imaging modalities have been developed for early detection of skin cancer and other inflammatory skin conditions such as psoriasis. Non-invasive modalities have been developed for skin imaging such as dermoscopy, full body imaging, in vivo reflectance confocal microscopy (RCM), OCT (Optical Coherence Tomography), among several others.

N. J. Dhinagar, Ph.D. Student, School of Electrical Engg. and Comp. Science, Ohio University, Athens, OH 45701 USA (e-mail: nd310510@ ohio.edu).
M. Celenk, Professor, School of Electrical Engg. and Comp. Science, Ohio University, Athens, OH 45701 USA (e-mail: celenk@ ohio.edu).

B. Literature Review

Early detection of cutaneous melanocytic lesions is important for a higher survival rate. Dr. Dhawan proposed [2] the dermoscopic imaging modality for examining skin lesions. The dermoscope allows for individual lesion based screening by enhancing dermoscopic structures - pigmentation and vascularity, that are not easily visible with the naked eye. Dermoscopy was commercialized by such companies as 3GEN LLC [3].

Nachbar et al. proposed the ABCD rule based on symmetry, border regularity, color variation, diameter of a skin lesion [4]. Subsequently, the Menzies method [5], and the three-point checklist by P. Soyer et al. [6] and Rigel et al. presented the importance of monitoring the change in skin lesions' features as diagnostic criteria [7]. Tsumura quantified skin image spatial information as two parameters - pigmentation and hemoglobin [8]. M. Sadeghi, A. Dhawan in [9], [10] model the pigmentation and vasculature of skin lesions, respectively. Pattern recognition systems developed to classify skin lesions include [11], [12], [13].

Maglogiannis [14] and a technical report [15] review the image features utilized for computer aided skin lesion analysis and the various skin imaging modalities, respectively. Some of the next generation sensing and imaging modalities for skin cancer detection include electrical impedance [16], ultrasound imaging [17]–[19], multispectral imaging [20], thermal imaging [21], and optical coherence tomography [22].

However, since this work [7] in 2005 there have been limited efforts towards tracking evolution of the lesion with time [23]. This paper proposes a framework to automatically monitor changes in a region of interest on the skin over time and predict its likelihood of developing into an anomaly

II. Proposed Skin Lesion Modelling

A. Sample Skin Images

Almost 2600 skin samples have been compiled for developing and validating the proposed framework.
Dermoscopic images from Menzies et al. as in Fig.1[24]; 1300 images from the Dermofit Image Library, University of Edinburgh, UK [25]; and 1279 from The International Skin Imaging Collaboration (ISIC) [26]. Follow-up skin images are obtained from Melafind [27] and high resolution ultrasound images of skin samples gathered from [19].

978-1-5090-1166-7/16/$31.00 ©2016 IEEE

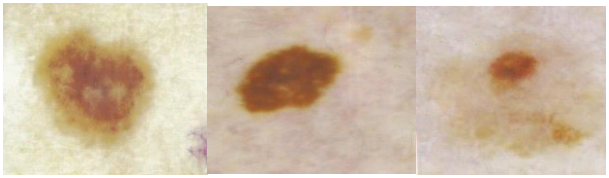

Fig. 1. L to R: Benign, Pre-cancerous and Malignant Melanoma [31].

B. *Flow Diagram of the Overall Approach*

As shown in Fig.2 its operation is explained in subsequent sections.

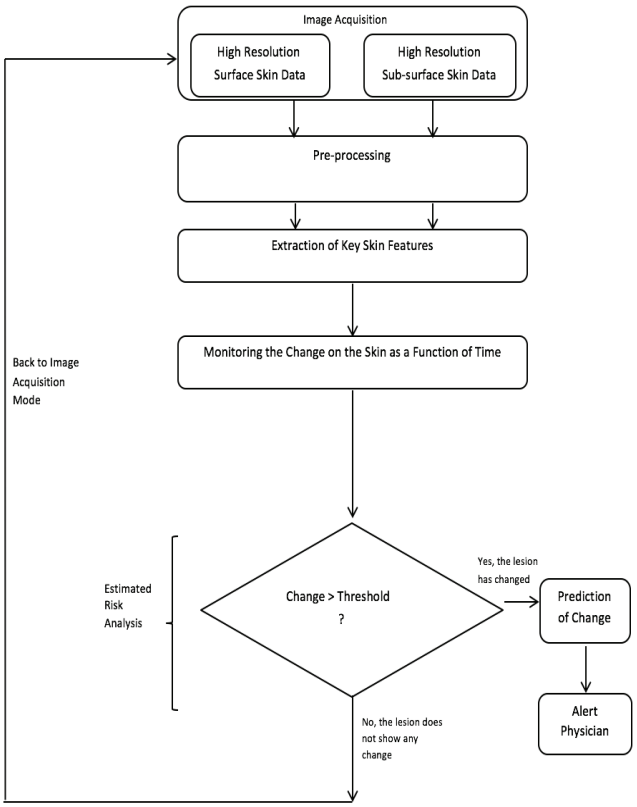

Fig. 2. Flow Diagram of the Design and Development of the Proposed Framework.

III. Technical Details of the Proposed Framework

A. *Pre-processing*

1. Image Resize: The input skin images are resized for optimal data resolution and processing speeds.

2. Image Enhancement: Artifacts on the skin; i.e., hair is isolated, filtered and subjected to illumination equalization.

3. Image Segmentation: Otsu's histogram based thresholding [28] is utilized for isolating the lesion from the surrounding skin for analysis.

4. Image Registration: The image frames are registered to be rotation, scaling and translation invariant.

B. *Extraction of Key Skin Features*

The key features extracted to define the spatial appearance of the lesion on human skin include - symmetry, border regularity, color, diameter (ABCD); differential surface structures [9]; and change of the subsurface structures. The vascularity and melanin content together contribute to the color component of the skin. The differential structures seen as pigment network, dots, globules and streaks can be represented by textural information.

1. Symmetry: Benign lesions usually tend to be symmetric about any axis through the centroid.

2. Border Regularity: The border of the benign skin lesions is regular.

3. Color: Vasculature of a lesion, erythema or the redness of the skin is a significant marker in cases of malignancy [29].

4. Diameter: Lesions with diameters greater than 6mm are seen as potentially malignant.

5. Differential Surface Structures: The presence of pigment network that is asymmetric about axes through the lesions' centroid is a key feature in malignancy.

6. Sub-surface Structures: Images acquired from high resolution ultrasound scanning are analyzed to measure the regularity of its subsurface layers (epidermis, dermis, and hypodermis) and lesion thickness below skin surface (Breslow's depth).

C. *Monitoring the Change on the Skin as a Function of Time*

1. Global Change Detection via Displacement Flow Vector Modeling

Spatial-temporal modelling governed by Eqns. 1 and 2 estimate the change in the skin images over different time frames where [u v] represents the progression in the lesion with time. This modelling approximates change in subsequent skin samples as piece-wise linear.

$$I(x, y, t) = I(x + \delta x, y + \delta y, t + \delta t) \quad (1)$$

where $I(x, y, t)$ is the image intensity – function of spatial co-ordinates x ,y and time t.

$$I_x \bullet u + I_y \bullet v + I_t = 0 \quad (2)$$

where I_x, I_y, I_t are the derivatives and $u = \frac{dx}{dt}$, $v = \frac{dy}{dt}$.

Eq. 2 is under constrained with two unknown's u and v, is solved by the Lucas-Kanade implementation [30] in Eq. 3. Eq. 4 is an optimization problem solved with the least squares solution by minimizing $\|AU - B\|^2$ to obtain U, where U = $[u\ v]^T$ and 'T' denotes transposition.

$$\begin{bmatrix} I_{x1} & I_{y1} \\ \vdots & \vdots \\ I_{xn} & I_{yn} \end{bmatrix} \cdot \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -I_{t1} \\ \vdots \\ -I_{tn} \end{bmatrix} \quad (3)$$

Eqn. (3) is represented by A, U and B as in Eq. (4).

$$\left.\begin{array}{l} \text{A} \bullet \text{U} = \text{B} \\ \min \ \|AU - B\|^2 \\ \text{U} = (A^T \cdot A)^{-1} \cdot A^T \cdot B \end{array}\right\} \quad (4)$$

The Lucas-Kanade displacement flow implementation is proposed for global change monitoring in follow-up skin images. Figs. 3 and 4 are displacement flow results capturing the spatial changes in the sample skin images from [24] and [19], respectively The growth of the lesion is visually indicated by the magnitude and direction of the vector flow result in Fig. 3. Fig. 4 also shows the displacement flow indicating the loss of uniformity in the sub-surface layers of the ultrasound images.

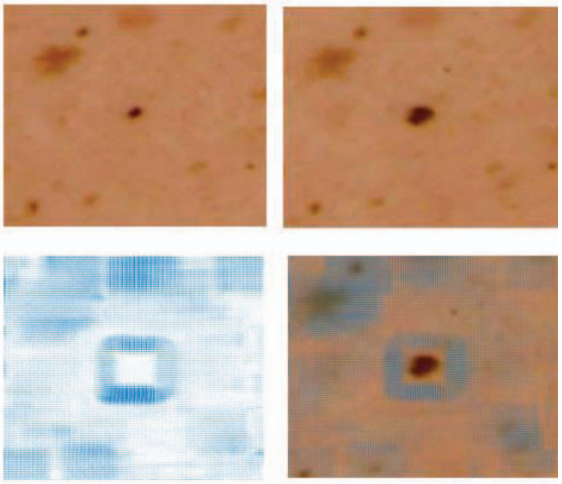

Fig. 3. Lesion Progression with Time for Surface Skin Image. In 2013 (Top Left), In 2015 (Top Right), Displacement Flow Result (Bottom Left), Super-imposed Change in the Lesion in 2015 (Bottom Right).

2. Estimated Risk Analysis

The skin images of a user at a given time is classified into high risk and low risk categories based on the severity of changes in the key features on the skin. High risk skin samples are marked and fed into the prediction module to estimate the future growth and change in the region of interest.

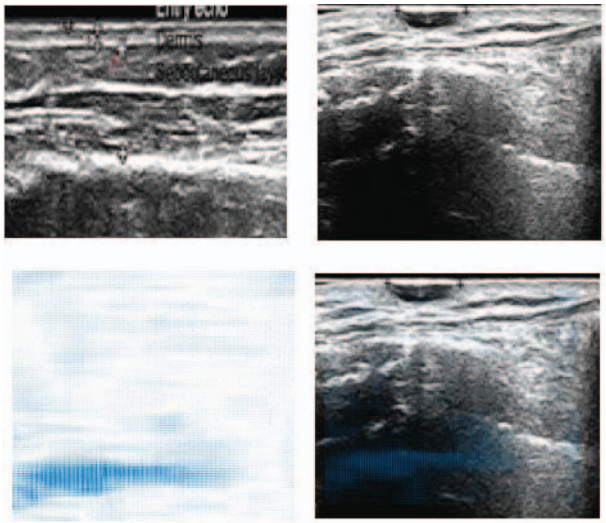

Fig.4. Lesion Progression with Time for Sub-Surface Skin Image. Normal Skin (Top Left), Benign Nevus (Top Right), Displacement Flow Result (Bottom Left), Super-imposed Change Below the Skin Surface (Bottom Right).

3. Predictive Change on the Skin

A prediction algorithm estimates the change in the evolving skin lesions. Fig. 5 is a simulation of the prediction algorithm to detect change as a function of time. The simulation shows a sharp rise in the change of the malignant lesion as compared to the change seen in a benign lesion.

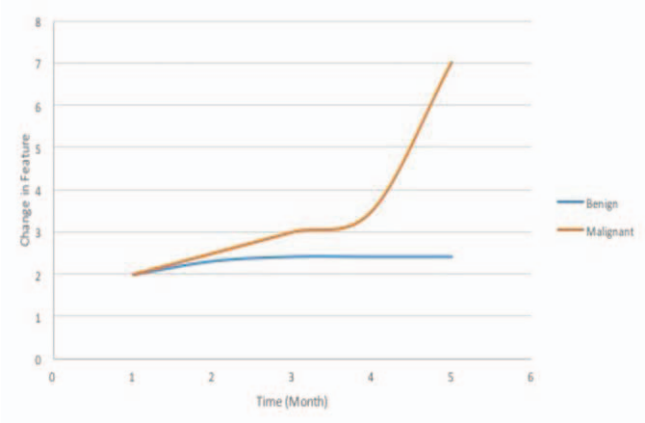

Fig. 5. Simulated Prediction Result for Change Detection in Benign (blue) and Malignant (red) Lesions.

IV. Conclusion and Future Work

Skin features such as ABCD, pigmentation, vascularity and sub-surface structures have been investigated as markers for skin conditions like melanoma. The proposed framework in this paper monitors the changes in these features, and predicts the severity of change over time. The framework is planned to be implemented as part of a diagnostic system for real-time analysis as illustrated in Fig.6. At the user side - images of the skin are uploaded to a smart phone via a graphical interface at different times. Advanced image analysis, change detection, prediction of change expected, could be carried out in a dedicated server. This paper

documents the preliminary results of the framework. Additional skin image data and local change detection is planned for further experimentation in order to verify the robustness of the work presented herein.

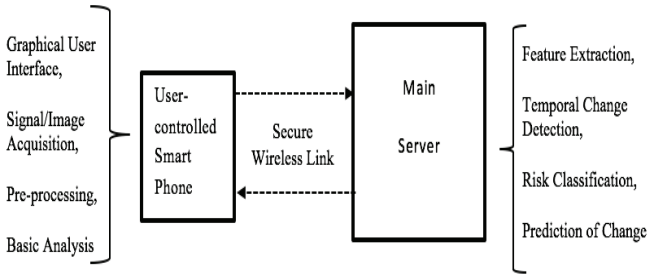

Fig. 6. Schematic of the Diagnostic System for Real-Time Analysis.

REFERENCES

[1] GP Guy Jr et al., "Prevalence and Costs of Skin Cancer Treatment in the U.S., 2002–2006 and 2007–2011," *Am. J. Prev. Med.*, vol. 48, no. 2, pp. 183–187, 2015.

[2] A. Dhawan, "Apparatus and Method for Skin Lesion Examination," 5146923, 1992.

[3] P. Arrazola, N. A. Mullani, and W. Abramovits, "DermLite II : An Innovative Portable Instrument for Dermoscopy Without the Need of Immersion Fluids," *Ski. Dermatology Clin.*, no. April, 2005.

[4] 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," *J. Am. Acad. Dermatol.*, vol. 30, no. 4, pp. 551–559, Apr. 1994.

[5] S. W. Menzies, C. Ingvar, and W. H. McCarthy, "A sensitivity and specificity analysis of the surface microscopy features of invasive melanoma.," *Melanoma research*, vol. 6, no. 1. pp. 55–62, 1996.

[6] H. P. Soyer, G. Argenziano, I. Zalaudek, R. Corona, F. Sera, R. Talamini, F. Barbato, A. Baroni, L. Cicale, A. Di Stefani, P. Farro, L. Rossiello, E. Ruocco, and S. Chimenti, "Three-point checklist of dermoscopy: A new screening method for early detection of melanoma," *Dermatology*, vol. 208, no. 1, pp. 27–31, 2004.

[7] D. Rigel, R. Friedman, A. W. Kopf, and D. Polsky, "ABCDE — An Evolving Concept in the Early Detection of Melanoma," *Arch. Dermatol.*, vol. 141, pp. 1032–1034, 2005.

[8] N. Tsumura, H. Haneishi, and Y. Miyake, "Independent-component analysis of skin color image," *J. Opt. Soc. Am. A*, vol. 16, no. 9, p. 2169, Sep. 1999.

[9] M. Sadeghi, M. Razmara, T. K. Lee, and M. S. Atkins, "A novel method for detection of pigment network in dermoscopic images using graphs.," *Comput. Med. Imaging Graph.*, vol. 35, no. 2, pp. 137–43, Mar. 2011.

[10] B. D'Alessandro and A. P. Dhawan, "3-D volume reconstruction of skin lesions for melanin and blood volume estimation and lesion severity analysis.," *IEEE Trans. Med. Imaging*, vol. 31, no. 11, pp. 2083–92, Nov. 2012.

[11] M. E. Celebi et al., "A methodological approach to the classification of dermoscopy images.," *Comput. Med. Imaging Graph.*, vol. 31, no. 6, pp. 362–73, Sep. 2007.

[12] S. Taheri, "Decision support system–Skin cancer," *Can. J. Image Process. Comput. Vis.*, vol. 2, no. 2, pp. 12–15, 2011.

[13] Q. Abbas et al., "Pattern classification of dermoscopy images: A perceptually uniform model," *Pattern Recognit.*, vol. 46, no. 1, pp. 86–97, Jan. 2013.

[14] 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, 2009.

[15] S. K. Parsons et al. , "Noninvasive Diagnostic Techniques for the Detection of Skin Cancers," *Eff. Heal. Care Progr.*, vol. 11, no. 11, 2011.

[16] P. Åberg, "Skin Cancer as Seen by Electrical Impedance," Karolinska Institutet, Stockholm, Sweden, 2004.

[17] C. C. Harland et al., "Differentiation of common benign pigmented skin lesions from melanoma by high-resolution ultrasound," *Br. J. Dermatol.*, vol. 143, no. 2, pp. 281–289, 2000.

[18] R. Kleinerman et al., "Ultrasound in dermatology: Principles and applications," *J. Am. Acad. Dermatol.*, vol. 67, no. 3, pp. 478–487, 2012.

[19] A. Mandava, P. R. Ravuri, and R. Konathan, "High-resolution ultrasound imaging of cutaneous lesions.," *Indian J. Radiol. Imaging*, vol. 23, no. 3, pp. 269–77, 2013.

[20] I. Diebele et al., "Melanoma-nevus differentiation by multispectral imaging," *Proc. SPIE-OSA Biomed. Opt.*, vol. 8087, p. 80872G–80872G–6, 2011.

[21] C. Herman and M. P. Cetingul, "Quantitative visualization and detection of skin cancer using dynamic thermal imaging.," *J. Vis. Exp.*, no. 51, pp. 3–5, 2011.

[22] V. R. Korde et al., "Using optical coherence tomography to evaluate skin sun damage and precancer.," *Lasers Surg. Med.*, vol. 39, no. 9, pp. 687–95, Oct. 2007.

[23] C. N. E. Anagnostopoulos, D. D. Vergados, and P. Mintzias, "Image registration of follow-up examinations in digital dermoscopy," *13th IEEE Int. Conf. Bioinforma. Bioeng. IEEE BIBE 2013*, pp. 7–10, 2013.

[24] S. Menzies, *Dermoscopy: An Atlas*, Third. McGraw-Hill Book Company, 2009.

[25] University of Edinburgh - UK, "DermoFit." .

[26] ISDIS, "The International Skin Imaging Collaboration." [Online]. Available: http://isdis.net.

[27] C. Melanoscan, "Melanoscan Example Images." [Online]. Available: https://www.facebook.com/245997470247/photos/pb.245997470247.-2207520000.1455306315./10152825347875248/?type=3&theater.

[28] N. J. Dhinagar, M. Celenk, and M. a. Akinlar, "Noninvasive Screening and Discrimination of Skin Images for Early Melanoma Detection," in *IEEE International Conference on Bioinformatics and Biomedical Engineering*, 2011, no. May, pp. 1–4.

[29] N. J. Dhinagar, "Analysis of Regularity in Skin Pigmentation and Vascularity by an Optimized Feature Space for Early Cancer Classification," in *IEEE EMBS International Conference on BioMedical Engineering and Informatics (BMEI 2014)*, 2014.

[30] University of Central Florida, "Optical Flow - Lucas Kannade." [Online]. Available: http://www.cs.ucf.edu/~gvaca/REU2013/p4_opticalFlow.pdf.