An improvement of skin aging assessment by non-invasive laser speckle effect: A comparative texture analysis

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***Abstract*— Skin aging is a complex biological process that is yet to be successfully modelled as it depends on various internal and external factors. This work therefore investigates novel low-cost skin aging assessment technique and equipment by using robust analysis of textural features unified with a laser-speckle imaging method, which is found to be quite capable of detecting multi-layer cellular textural changes exhibited by the biological skin aging process. This study and low-cost product seem to be the first of its kind, which is expected to bring great benefit to both healthcare and cosmetic sectors.**

I. Introduction

Skin aging is a complex biological process which affects different skin layers, structures and components. Particularly, in the basal layer (*stratum basale*) many remarkable age-related changes may occur such as the size of cells which are called *"basal keratinocytes*" [1]. The other age related changes are also observed in skin blood flow and skin blood content (blood capillary loops) [2].

Modelling of skin aging process is important in many different aspects including skin health and cosmetics [1, 3, 4]. This can help better understand skin growth, damage and diseases as well as manage personalized care of skin.

The motivation and hypothesis behind our work are therefore as follows: One of the major textural changes through the skin aging process occurs in the cell sizes at the basal layer [1] which is located at approximately 0.1*mm* depth of the skin. It was reported that Red laser light (λ=650 micron) can penetrate up to 2*mm* downward inside the skin [5] and may interact with those cells (*basal keratinocytes)* to generate cellular textural effects due to cell network. These textural forms normally convey indirect information about the changes in cell size and their structural characteristics by the series of comparative observations. The other textural changes in blood flow (affecting the textural intensity of blood cells) were studied by Ryan [2]. It was concluded that over an age group from 20 to 72 skin blood flow falls by 40% by aging. In addition, the Red laser light used in our earlier tests is found to have optimal wavelength of 650μm for red blood cells reflections to detect them [3, 6]. These textural forms of skin images are built due to laser speckle phenomenon, but do not directly provide any absolute information of cell size or its structure, hence should be evaluated comparatively between the samples.

This work therefore aims to bring low-cost and non-invasive solutions to accurate and reliable assessment of skin-aging process by a laser-optical and textural analysis of sub-skin layers exploiting the textural characteristics of the skin as the most of skin tissues are in textural form including skin cells and micro blood vessels.

This study is the extension of our group's earlier successful study on novel and robust skin modelling for the diagnosis of skin abnormalities, which was achieved by combining light back-scatter and laser speckle imaging [3]. The proposed method and equipment are quite cost-effective alternative to some functions of high-cost confocal microscopy (being around $100K) or similar expensive instrumentations [3]. The methods are not aimed at substituting all aspects of such high-cost instruments. However, it will be effectively used to undertake some of their important functions to assess skin aging progress at earlier stages by means of such a low-cost reliable and easy-to-use instrumentation and method, which is one of the most desirable components of current healthcare systems around the world. To the best of our knowledge, this pilot study is the first of its kind, and the method and low-cost equipment developed are expected to have a great potential in both healthcare and cosmetic sectors.

II. Methods and Materials

To prove the above hypothesis, 136 participants at broad range of age groups (between the ages of 19 and 60) have been selected to collect skin data set by utilizing two different techniques, namely (i) laser speckle imaging and (ii) back scatter readings of RGB/IR bands. For both types of data sets, exactly the same group of participants and same train/test sets are used in order to perform an accurate and consistent comparison.

Laser speckle technique is used to unveil textural response from the changes in basal layer cells due to skin aging progress. Meanwhile, normal RGB/IR lights are used to demonstrate that the cellular changes in basal layer is only associated with the textural analysis of laser speckle effects rather than any basic light reflection from skin surface or sub-surface. This is so even though the normal

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light has the same penetration distance into the skin (2 *mm*) and hence its effect is not sufficient to detect any skin change due to skin aging.

A. Skin Aging Data Set

The values in the data set have been calculated from 9 types of textural measures (explained in Section *C*) for two types of window sizes applied on the selected (120*x*120 pixel) image segment area at two different locations of each laser speckle image (brighter and darker regions of laser illuminated area on the skin surface).

The data set contains a total of 136 independent cases of laser speckle measurements from the participants and contains 22 total extracted attributes, which include 9 texture measures *x* 2 types of pixel windows (*3x3, 5x5*) of laser speckle and 4 RGB/IR readings. Same sampling of skin areas for each participant is used also for back-scatter measurements.

The data set was built in the following order: 1) The images of laser light illumination causing a speckle effect on the skin areas were taken by a CCD camera; 2) Two image segment areas at two certain locations of each laser speckle image were chosen for two different speckle characteristics; 3) Each texture measure was applied onto each image segment area one by one to calculate statistical textural values; 4) RGB/IR light back scatter readings were made on the same skin area of the same participants. The total size of data set is then *136 samples x 22 features*.

B. Laser speckle imaging

Laser speckle imaging is a well-known method [7][8] which is widely used in skin based medical applications such as capillary blood flow in skin layers[9] and skin modeling [3]. In our experiments, a specifically designed device is used to collect laser speckle images of the skin samplings. Since the results obtained by the different image analyses and Bayesian classification are used for comparative works, the quality or minor error content of the optical components of the system such as laser stability and lens distortion are not important for this study, hence may be ignored.

C. Imaging Equipment

A modified commercial digital CCD camera with the resolution of 3840*x*2880 is used for laser speckle image data collection as depicted in Fig.1. An optical modification is made on its objective for a close-range image acquisition with non-auto focus ability to keep the geometry of images at constant level. A red laser source is attached to the camera so that it illuminates approximately 10*mm* diameter area of interest on forearm skin of each participant at 23^{o} of angle to the skin surface normal (directed by interior surface-coated mirror) to generate speckle effect (Fig.2).

The laser source is low level (1mW) collimated red laser (λ=650 micron) whose power is much less than maximum permissible exposure (*MPE*) which is 2000 Wm^{-2} for human skin for an exposure time 5-10 hours. The exposure time of laser used is only 3-5 seconds. For this comparative work, RGB/IR light back-scatter data collection from the sub-skin layers is also accomplished by utilizing a set of instruments. Each instrument contains transmitter diode and receiver sensor to measure the back-scatter intensity level after they are calibrated to avoid the environmental light effects.

Fig.1. Laser speckle image recording *CCD* camera with *red* laser illumination facility (λ=650 micron). On the image a single pixel refers to 2.8 μm. The textural form of laser speckle effect image segment of skin is shown on the top-left corner.

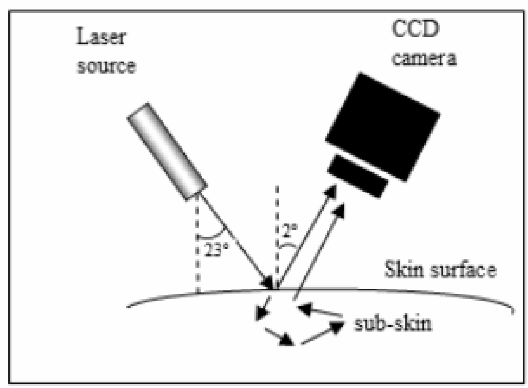

Fig.2. The optical components of the proposed system for laser speckle image data collection by skin sampling.

D. Texture analysis algorithm

In the experiments, for the texture based quantization process of skin related laser speckle images, five statistical measures are used, which were derived from the Phillips's work [10]. Each texture's statistical characteristic is applied onto two different sizes of operation windows (3*x*3 and 5*x*5) which correspond to Eqs. 1-4 and single measure at only *3x3* window size corresponds to Eq.5. Each textural measure has been applied on two 120*x*120 pixel areas on each laser speckle image. As far as such texture analysis is concerned, large window size produce large edge effect at the class edges but provide more stable texture measures than small windows. In return, small window size is less stable but has smaller edge effect [11].

The texture measures can be extracted by using the mathematical expressions as given Eqs.1-5;

$$Variance_{Russ} = \sqrt{\sum (centerpixel - neighbor)^2} \quad \text{(Russ)} \quad (1)$$

$$Variance_{Levine} = \frac{1}{area} \sum (centerpixel - mean)^2 \quad \text{(Levine)} \quad (2)$$

$$\sigma = \sqrt{Variance_{Levine}} \quad \text{(Sigma)} \quad (3)$$

$$Skewness = \frac{1}{\sigma^3} \frac{1}{area} \sum (centerpixel - mean)^3 \quad \text{(Skewness)} \quad (4)$$

$$Std.Deviation = \sqrt{\frac{\sum (x - x')^2}{n}} \quad \text{(Std. deviation)} \quad (5)$$

The measure (Eq.5) "*standard deviation*" indicates the pixel-intensity based statistics of the textural image.

E. Bayesian Classifier

The efficiency of Bayesian classifier models has been demonstrated in the previous works for bio-medical data analysis [12, 13]. For example, it was used for skin lesion classification with a predictive accuracy of 90% [14] and for a successful laser speckle image analysis [3].

Bayesian networks also have useful properties in which a graphical representation of the interaction between the attributes can be observed. In Bayesian networks, each attribute is represented by a node and connected to each other with a link if there is substantial information flow between these two attributes. In Bayesian networks, each node represents a database attribute and is called a variable. The connections (arcs) between the nodes represent dependency relationships of variables. Bayesian networks are very efficient tools for modeling the joint probability distributions of variables. For example, if A = $\{X_1,\ldots X_n\}$ is a random variable which denotes patterns spanning n=NxM dimensional vector space, the joint probability distribution P=$(X_{1,\ldots}X_n)$ is then a product of all conditional probabilities and may be expressed in Eq.6

$$P(X) = \prod_i P(X_i | pa(X_i)) \quad (6)$$

where pa(X_i) is the parent set of X_i. In order to realize the Bayesian classifier and network, PowerPredictor™ utility was utilised.

III. RESULTS AND DISCUSSION

In the experiment, a classification model is built as to distinguish two age groups, namely, a and b that represent the subjects who are younger than 30 years of age and older than 30 years of age, respectively. The textural measures and laser-speckle images were used as a feature set to characterize the subjects.

The data was divided into training and test cases consisting of 2/3 and 1/3 of the samples, respectively. This is usually carried out in order to assess generalization ability of the method. The classification model was built over the training cases and subsequently tested on the testing cases by utilizing the Bayesian classifier, for which *PowerPredictor*™ tool was used.

The initial results are promising and show that the Bayesian classifier built on three of the twenty two attributes is well capable of distinguishing these two age groups (a and b) with a classification accuracy of 74%. The confusion matrix in Table I also shows a balanced classification result over these two classes, which suggests that the method can be generalized over both age groups.

The Bayesian network was also constructed using the three stratified features as given in Fig. 3. In Fig.3, the "age category" is the class node used to distinguish between the two age groups a and b, and the connected nodes (attributes) are the texture measures, two of which seem to have higher predictive power. They are

skew1: *3x3* pixel operation window applied on *120x120 pixel* segment in darker (*ir2*) laser speckle image area.

skew2: 5*x5* pixel operation window applied on *120x120* pixel segment in brighter (*ir1*) laser speckle image area.

levine2: it is found to have only indirect effect on classification process and hence may be disregarded.

TABLE I
CONFUSION MATRIX WITH PREDICTIVE ACCURACIES (%) AS A RESULT OF THE BAYESIAN CLASSIFIER

Classes	a (age<30 years)	b (age>30 years)
a (age<30 years)	73%	25%
b (age>30 years)	27%	75%

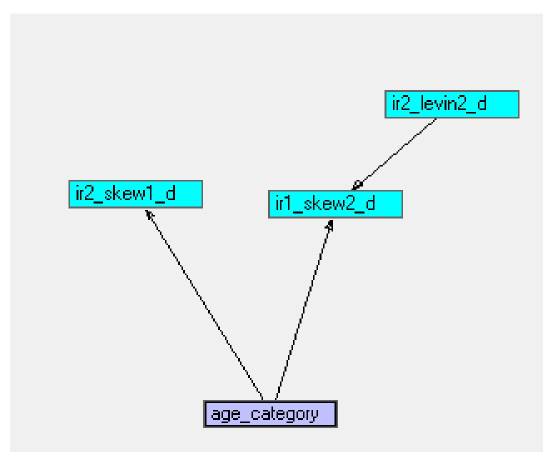

Fig.3. Bayesian network built with three stratified features after training with the textural laser speckle data set. The other 22 nodes are excluded by training process and are not shown here. The direction of links (arrows) can be neglected due to specification of graphics utility.

The classification results obtained with 74% accuracy may depend almost entirely on the textural characteristics of laser light formed due to an interaction with the cellular network at the *basal layer* of skin or textural form of blood cells at the top layers of dermis (e.g., *papillary dermis*). To prove this hypothesis, exactly the same participants and the same ratio of training/test data sets, collected on the same skin location (forearm) with the laser ones were used for RGB/IR back scatters readings. As a result of this analysis, predictive accuracy was found to be 51%. This lower accuracy suggests that the pinpoint light back scatters seem to be unable to distinguish two age groups (a and b). This is because a RGB/IR led light source and its single reflection reading by a receptor provides an average scatter value of specific skin volume, hence its resolution is not sufficient for such analysis at cellular level.

IV. CONCLUSIONS

The study presented in this paper introduced a cost effective and non-invasive unified technique to be used in not only skin based researches carried out by the academic institutions but also the assessment of skin health by healthcare and cosmetic practitioners, who cannot afford high-cost instrumentations such as confocal microscopy. The proposed work exploited the flexible characteristics of lasers, image processing techniques like texture analysis and Bayesian networks to achieve its target. It also demonstrated a substantial improvement of laser based techniques over the conventional RGB/IR lights for skin aging analysis to support the similar works. The proposed work provides an advantage of cost-effectiveness and practicality of rapid inspection over the high-cost microscopy techniques [1] which are currently used for the analysis of skin-aging process.

To the best of our knowledge, this successful pilot study is the first of its kind, and the computational method and low-cost equipment developed have resulted in a promising result that demonstrates the capability of accurately distinguishing the two age groups, and are therefore expected to have a great potential in both healthcare and cosmetic sectors. Further study will therefore be geared towards two directions (1) to improve the predictive accuracy by developing new characteristic features of skin and improving image processing methods and (2) to be able to predict actual skin age, which is expected to play a key role in personalized skin care.

REFERENCES

[1] A.N. Rice, “Laser microscopy tests for skin damage,” *BioPhotonics*, 2013.

[2] T. Ryan, “The ageing of the blood supply and the lymphatic drainage of the skin,” *Micron*, vol. 35, no. 3, pp. 161–171, 2004.

[3] A.B. Orun, E. Goodyer, H. Seker, G. Smith and V. Uslan, “Optimized parametric skin modelling for diagnosis of skin abnormalities by combining light back-scatter and laser speckle imaging” (Accepted for publication) *Skin Research and Technology*, 2014.

[4] C. Longo, A. Casari, F. Beretti, A.M. Cesinaro, and G. Pellacani, “Skin aging: In vivo microscopic assessment of epidermal and dermal changes by means of confocal microscopy,” *Journal of the American Academy of Dermatology*, vol. 68, no. 3, pp. e73–e82, 2013.

[5] A.N Bashkatov , E.A. Genina, V.I. Kochubey and V.V. Tuchin, “Optical properties of human skin,subcutaneous and mucous tissues in the wavelength range from 400 to 2000nm,” *J. Phys. D: Appl. Phys*.,vol.38, pp.2543–55, 2005.

[6] K.R. Forrester, “Blood-flow imaging adapted for endoscopy,” *Biophotonics International*, 2003.

[7] G. Mahé, P. Rousseau, S. Durand, S. Bricq, G. Leftheriotis, P.Abraham, “Laser speckle contrast imaging accurately measures blood flow over moving skin surface,” *Microvascular Research*, vol. 81, no. 2, pp.183-188, 2011.

[8] C.S. Agarwal, J. Allen, A. Murray, I. F. Purcell, “Laser Doppler assessment of dermal circulatory changes in people with coronary artery disease,” *Microvascular Research*, vol. 84, no. 1, pp. 55-59, 2012.

[9] J.D. Briers and S. Webster, “Laser speckle contrast analysis (LASCA): a non scanning, full-field technique for monitoring capillary blood flow” *Journal of Biomedical Optics*, vol. 1, no. 2, 1996.

[10] D. Phillips, “Image Processing in C, Part 15: Basic texture operations ,” *C/C++ Users Journal*, Nov. 1995.

[11] J.S. Christoper and T.A. Warner, “Scale and texture in digital image classification,” *Photogrammetric Engineering & Remote Sensing*, vol. 68, no. 1, pp. 51-63, 2002.

[12] A. Celebiler, H. Seker, B. Yuksel, A.B. Orun, S. Bilgili and B. Karaca, “Discovery of connection between Age Related Macular Degeneration, MTHFR C677T and PAI 1 4G/5G gene polymorphisms and body mass index by means of Bayesian inference methods,” *Turkish Journal of Electrical Engineering and Computer Science*, vol. 21, pp.2062-78, 2013.

[13] A.B Orun, and H. Seker, “Development of a computer game-based framework for cognitive behaviour identification by using Bayesian inference methods”, *Computers in Human Behavior*, vol. 28, no. 4, pp. 1332-41, 2012.

[14] A.B Orun and N. Aydin, “Variable optimisation of medical image data by the learning Bayesian Network reasoning”, *Proc. of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Buenos Aires, Argentina, 2010.