Texture based characterization of sub-skin features by specified laser speckle effects at λ=650nm region for more accurate parametric "skin age" modelling

Orun, A., H. Seker, V.Uslan, E.Goodyer and G. Smith

Abstract

Objective: The textural structure of "skin age" related sub-skin components enables us to identify and analyse their unique characteristics, thus making substantial progress towards establishing an accurate skin age model. **Methods:** This is achieved by a two stage process. First by the application of textural analysis using laser speckle imaging, which is sensitive to textural effects within the λ=650 nm spectral band region. In the second stage a Bayesian inference method is used to select attributes from which a predictive model is built. **Results:** This technique enables us to contrast different skin age models, such as the laser-speckle effect against the more widely used normal light (LED) imaging method, whereby it is shown that our laser speckle based technique yields better results. **Conclusion:** The method introduced here is non-invasive, low-cost and capable of operating in real-time; having the potential to compete against high-cost instrumentation such as confocal microscopy or similar imaging devices used for skin age identification purposes.

Introduction

The cellular structure of sub-skin features such as cells at the basal layer called "basal keratinocytes" or blood capillary loops may enable us to exploit texture based algorithms to identify their unique characteristics to predict skin age higher accuracy than conventional image analysis techniques. The method would lead to more accurate skin age identification without the need for high-cost comprehensive imaging instrumentation. As presented by previous researchers [1][2] skin age depends on physical characteristics of sub-skin features such as basal keratinocytes cells, skin blood flow and blood capillary loops. These features can normally be examined by very comprehensive instruments including confocal microscopy [6], high resolution *IR* imaging systems, photoacoustic tomography etc. whereas in our work an alternative skin age prediction process can be accomplished by the application of cellular textural analysis in association with a low-cost laser speckle imaging method specified at the 650nm spectral band region, comprehensive texture analysis and the use of machine learning tools like Bayesian networks (BN) [19][20] or SVM[17][18]. Our previous experiments [3][4][5] demonstrated that such a unified method which comprises the above utilities may be capable of identifying the subtle skin abnormalities such as the early stage of skin moles, skin disorders or skin damages, etc. The different variants of applying this method to analyse skin features only necessitate the re-selection of laser wavelength, power and system geometry, without the need for any substantial change in methodology.

Skin ageing is a complex biological process which affects different skin layers, structures and components. Modelling of skin ageing process is important for many different aspects including skin health and cosmetics [1][3][6]. This can help better understand skin growth, damage and disease as well as the management of personalised skin care. The motivation and hypothesis behind our work are therefore as follows: One of the major textural changes through the skin ageing process occurs in the cell sizes at the basal layer [1] which is located at approximately $0.1mm$ skin depth. It was reported that Red laser light (λ=650 nm) can penetrate up to $2mm$ downward into the skin [8] and may interact with these cells (*basal keratinocytes)* to generate cellular textural effects due to cell network structure. These textural forms normally convey indirect information about the changes in cell size and their structural characteristics, by the series of comparative observations (e.g. different skin age classes). The other textural changes which arise from blood flow (due to textural intensity of blood cells) was studied by Ryan (2004) [2]. It was concluded that over an age group from 20 to 72 skin blood flow falls by 40% by ageing. In addition, the Red laser light used in our earlier tests was found to have an optimal wavelength of 650 nm to detect reflections from red blood cells [3]. These textural forms of skin images are built using the laser speckle phenomenon, but it does not directly provide any absolute information of cell size or its structure, hence the images should be evaluated comparatively between class samples. Similar non invasive techniques used for skin age prediction process are usually based on characterisation of skin surface features (e.g. wrinkles, etc.) using (non-laser) normal light sources [7]. Kyungrok et al. [9] and

Hayashi et al. [10] presented findings of skin age estimation by using the wrinkle features of skin. The works yield reasonable results of age estimation to some extent, but their methods only rely on skin surface geometry and hence quite superficial in comparison to our broader range modelling. The remarkable advantage of our new method over the above ones is demonstrated by our experimental results in later sections. Our work introduced here aims to bring low-cost and non-invasive solutions to deliver accurate and reliable assessments of the skin-ageing process by a laser-optical and textural analysis of sub-skin layers, exploiting the textural characteristics of the skin as the majority of skin tissues can be visualised 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 laser speckle imaging and texture analysis [3]. The cost-effectiveness is the major advantage of the system, as it consists of one ordinary digital camera (about 50-100 USD) and a laser pointer (5-10 USD). Whereas the similar alternative systems such as Laser Speckle Contrast Analyser (LASCA), confocal microscope (which cost between 50K – 100K) or Raman spectroscope prices about 10K-30K USD. [3]. The methods are not aimed at substituting all aspects of such high-cost instrumentation. However, it will be effectively used to undertake some of their important functions to assess skin ageing 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 yielding better results than normal light (e.g. *LED*) based methods, and its low-cost and non-invasive characteristics are expected to have a great potential in both healthcare and cosmetic sectors.

Methods and materials

a) Data sets for laser based and normal light imaging

In our study 122 participants aged between 18 and 60 years are examined using laser and normal light (LED) image data sampling methods (Figure 1). The classification model is built to distinguish between two age groups, representing subjects who are younger than 30 years of age (group A) and subjects older than 30 years of age (group B). 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 specific locations of each laser speckle image were chosen for analysis by two different speckle characteristics being small and large texture primitives; 3) Each texture measurement was applied to each image segment area one by one to calculate statistical textural values; 4) same texture measurements were applied to the skin surface image segments taken under normal light illumination. The total measurement set consisting of being 27 attributes (18 for laser speckle imaging and 9 for normal light).

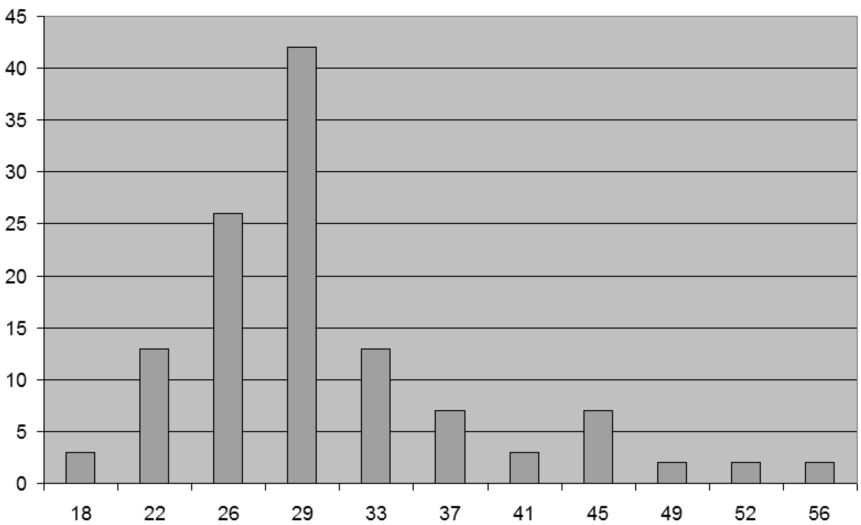

Figure 1. The age distribution histogram of participants used for image data sampling collection Where the majority group shown is aged 29.

For data collection, forearm region is used for the ethical convenience (e.g. forearm is less risky than forehead for a danger of laser exposure to the eyes) but forearm is not particularly selected for a physiological reason. This is because, to the best of our knowledge, no any evidence exist in the literature that, a particular body location yields best results for laser speckle method, as almost all past “skin age” studies were based on normal light other than laser light with its speckle effects.

b) system configuration

The physical characteristics of laser speckle effect is very sensitive to the optical system geometry, particularly incident light and reflection angles. These angles must always be kept constant for each measurement for accurate results, where in our case they are $\alpha = 23^{o}$ for incident light and $\beta = 2^{o}$ for reflected light from the skin surface respectively. The complete system configuration is shown in Figure2.
The incident and reflection angles are selected randomly (at the system’s manufacturing stage) in the system configuration and always kept constant. Hence they are not specifically selected at a certain degree. This is because the Laser speckle imaging (LSI) method is “comparative” rather than quantitative one. The only important factor is that the all skin LSI measurements have to be done in the same geometric conditions with same angular configuration.

Imaging Equipment

A modified commercial digital CCD camera with a resolution of 3840*x*2880 is used for laser speckle image data collection as depicted in Figure 2. On the image a single pixel refers to 2.8 μm. An optical modification is made on the objective for 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 such that it illuminates approximately 10*mm* diameter area of interest on the 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. The laser source is a low level (1mW) collimated red laser (λ=650 nm) whose power is much less than maximum permissible exposure (*MPE*) being 2000 Wm^{-2} for human skin for an exposure time 5-10 hours. The exposure time of the laser used is only 3-5 second. For comparison, White light back-scatter data collection from the sub-skin layers is also accomplished using a single LED illumination. The CCD camera objective aperture has been specifically designed such that the environmental light changes do not affect the imaging process adversely. The camera position is kept constant (approximately 2^{o} degree to skin surface normal) during the image acquisition of both sampling categories for an accurate comparison.

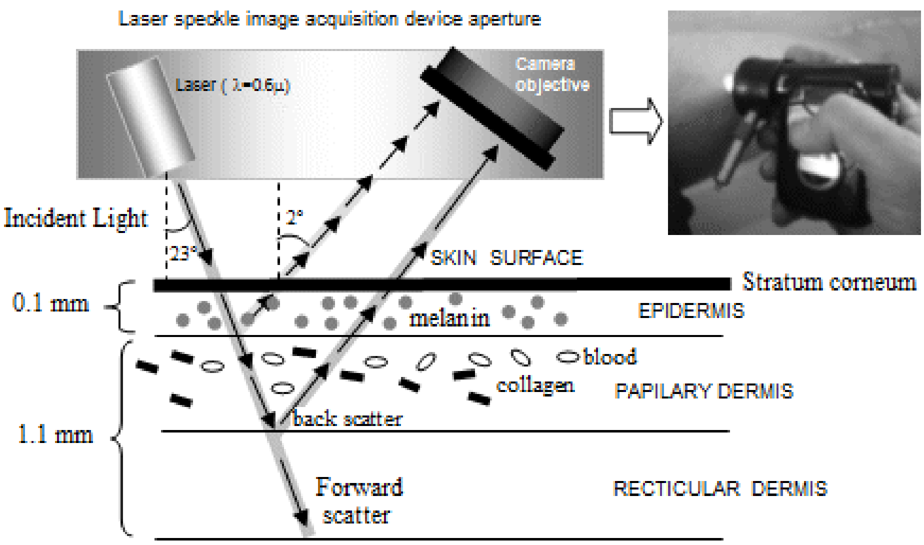

Figure 2 - Laser light behavioural characteristics through the skin layers. Minor and major back scatters are represented by short and long arrows respectively where the most skin age parameters are located at 0.1mm depth of skin. Since the reflected laser light conveys mixture of different skin component information simultaneously, an efficient discrimination method has to be utilized to separate them. (e.g. laser wavelength whose interaction is specific to the target skin component)

b) Laser speckle imaging

Laser speckle imaging is a well-known method [13][14] and is widely used in skin based medical applications such as capillary blood flow in skin layers[15] and skin modelling [3]. In our experiments, a specifically designed device is used to collect laser speckle images of the skin samplings. Since the geometric configuration of imaging devices may vary broadly, the laser speckle technique is based on comparative analysis rather than absolute measurements. Hence the quality or minor error sources for the system such as environmental lab conditions, lens distortion, etc. are common and may be ignored. The laser speckle effect is based on a physical phenomenon whereby coherent light (e.g. laser) scattered from a collection of randomly distributed particles (e.g. coarse glass surface) generates a characteristic random interference pattern which is called The Laser Speckle pattern. Briers and Webster [15] formulated the laser speckle contrast as:

$$\text{Speckle Contrast } \mathbf{K} = \sigma_S / \langle I \rangle \qquad (1)$$

Where K is speckle contrast ($0<K<1$) whose ideal value is 1. σ_s is the standard deviation of the spatial intensity variations in the speckle pattern. $\langle I \rangle$ can be taken as a spatial average.

c) Texture analysis method

The values in the data set have been calculated from 9 types of textural measures [11] for two types of window sizes applied on the selected (*120x120* pixel) image segment areas 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 122 independent cases of laser speckle measurements from the participants and contains 27 total extracted attributes, which include 9 texture measures *x* 2 types of pixel windows (*3x3, 5x5*) of laser speckle and 9 normal light (*LED* illuminating) texture measures. 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 [12]. The texture measures used are shown by Formulas 2-6 in Figure 3.

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

$$Variance_{Levine} = \frac{1}{area} \sum (centerpixel - mean)^2 \qquad \text{(Levine)} \qquad (3)$$

$$\sigma = \sqrt{Variance_{Levine}} \qquad \text{(Sigma)} \qquad (4)$$

$$Skewness = \frac{1}{\sigma^3} \frac{1}{area} \sum (centerpixel - mean)^3 \qquad \text{(Skewness)} \qquad (5)$$

$$Std.Deviation = \sqrt{\frac{\sum (x - x')^2}{n}} \qquad \text{(Std. deviation)} \qquad (6)$$

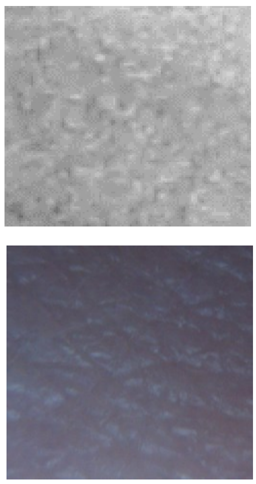

Figure 3 - laser speckle (top-right) and normal light (bottom-right) skin image samplings subject to texture analysis by (3x3) and (5x5) pixel window size calculation process by different (2-6) texture measures (on the left)

Any textural image (image segment) should contain very regular and homogenous textural content, having sufficient texture primitives for a statistical process. These two conditions (homogeneity and sufficient texture content) can be justified for only some restricted parts of a Laser speckle image but not for the whole image due to non-homogeneity . In addition to these requirements, more than one type of samplings have to be selected on different energy band regions (different level of laser light scatterings) on the same image to increase skin content information conveyed by the skin-penetrating laser light.

d) Bayesian Networks

Bayesian networks are useful methods by which very comprehensive data analysis can be made [19][20]. Bayesian network graphical representations of the interaction between the attributes can also be observed. In Bayesian networks, each attribute is represented by a node which is connected to another node with a link if there is substantial information flow between these two attributes. 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 the 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.7

$$P(X) = \prod_i P(X_i | pa(X_i)) \qquad (7)$$

Where $pa(X_i)$ is the parent set of X_i. In order to accomplish the Bayesian classifier network construction, PowerPredictor™ utility was used within the experiments. The Bayesian networks tool used within the system, yields a maximum classification accuracy by use of two classes (two age groups) which performs better than three or more classes. Within this work the priority is given to classification accuracy rather than a larger scale of age groups. However such sort of balance would be kept easily or adjusted optionally in the bayesian tool setup by the selection of different parameters (number of group v classification accuracy) as this reflects the nature of statistical classifiers. Within this work Bayesian tool is preferred over the other classifiers since it exhibits a graphical representation of cause-effect links between the data attributes to interpret more easily. Here Bayesian classifier is used with its specific parameters (specified in classification results section) for the classification of whole data set that consists of textural analysis values for each laser speckle image segment. The whole data set (with 122 participants) is divided by the two classes of age groups whose distribution numbers can be seen in the histogram (Figure 1), then each class is further divided by training and test sets by the ratio of 3/2 approximately.

Results and discussion

Optimization of Light type and texture measure

For the tests we have used two types of data sets C) laser speckle based image texture analysis D) normal light (white colour *LED*) based image texture analysis, for comparison to justify the discrimination advantage of the laser speckle phenomenon over the normal light (LED). The optimum texture measures are also selected automatically by Bayesian classification utility shown in Figure 4 and the distinct advantage of laser light over the normal one is proven by the test results presented in the following sections.

Bayesian Classification results

The comparison between our unified method based of laser-speckle imaging, and the conventional normal light based method is made by using Bayesian network (BN) classification tool (PowerPredictor™). The results show that laser speckle method (Figure 4) has distinct advantages (classification accuracy = 78%) over the light based method shown in Figure 5 (classification accuracy = 57%), where for one-to-one comparison, exactly same conditions such as; the same training/test sets and BN parameters (e.g. threshold (*t = 0.1*), discretisation method (*equal frequency*), same texture measure (*skew(3x3),* etc.) are used. In the classification process two age categories (a < 30 and b > 30) are used.
The Confusion matrix as shown in Table 1, includes both laser speckle and normal light based analysis for a comparison of both methods whose classification accuracies are 78% and 57% respectively. In the table even though the normal light based analysis exhibits a value of 84% for cross match of Classes A vs. A, which is close to laser speckle one (89%), it shows much lower performance (28%) for cross match of its Classes B vs. B in the table.

TABLE I . CONFUSION MATRIX WITH PREDICTIVE ACCURACIES (%) AS THE RESULT OF BAYESIANCLASSIFIER

classes	Laser speckle analysis		Normal light based analysis	
	A (age<30 years)	B (age>30 years)	A (age<30 years)	B (age>30 years)
A (age<30 years)	89%	33%	84%	72%
B (age>30 years)	11%	67%	16%	28%

Results of laser-speckle image based configuration

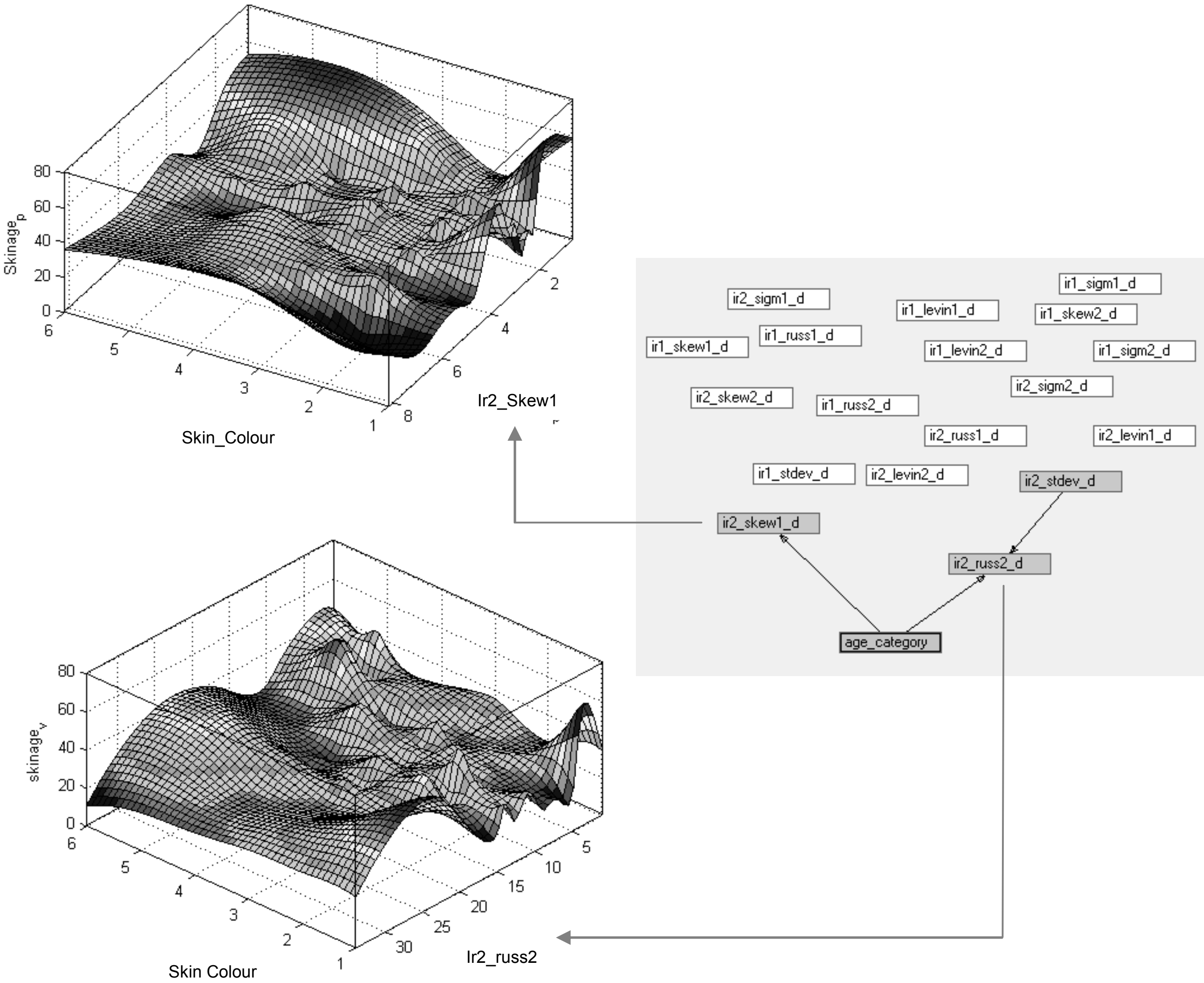

Figure 4 – For laser speckle skin imaging based model construction, the best predictive texture measures are used (r2_skew1 and ir2_russ2) which are automatically selected by Bayesian inference tool PowerPredictor™ during the classification process (right image). The nodes left disconnected automatically are those whose contributions would not change the accuracy results. For the surface fit process Interpolant method with bi-harmonic (v4) is used yielding the goodness-of-fit results as : *r2_skew1* : SSE = 4.023e-022 and *ir2_russ2* : SSE = 3.827e-023. The model is also based on assumption that there is biologically close correlation between the normal age and the skin age.

Results of normal light (*LED*) image based configuration

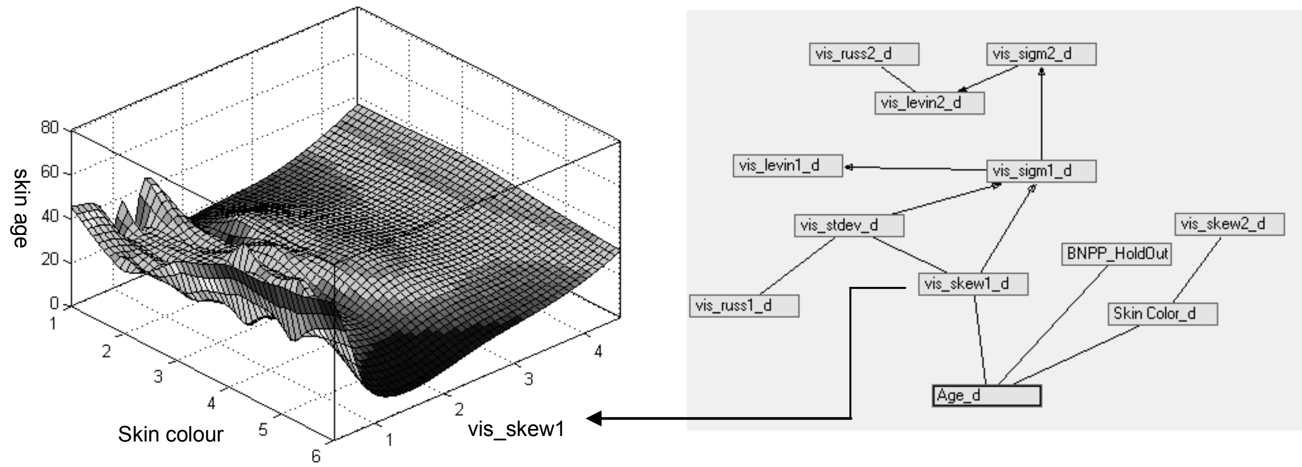

Figure 5 - For normal light *(LED*) skin imaging based model construction (right image), the best predictive texture measure is used (vis_skew1) which is automatically selected by bayesian inference tool PowerPredictor™ (left image). For the surface fit process Interpolant method with bi-harmonic(v4) is used yielding goodness-of-fit result : SSE = 7.07e-022. The model is based on assumption that there is biologically close correlation between the normal age and the skin age

The goodness of fit indicator : $SSE = Sum_{(i=1 \text{ to } n)}\{w_i\ (y_i - f_i)^2\}$. In the formula y_i : observed data value and f_i : predicted value from the fit. w_i : weighting (applied to each data point and it is usually 1). A value closer to 0 indicates that the model has a smaller random error component, and it means that the fit will be more useful for prediction

Conclusion

Laser speckle imaging method yields a better "*skin age prediction*" results than normal (*LED)* light imaging technique. This may be due to specific characteristics of laser light, having more condensed energy and constant (stable) wavelength than normal light. Its nature also necessitates a high level of interaction with sub-skin components (e.g. textural cellular or blood loops network of skin) which causes speckle effects whose parameters are specific to the physical aspects of a skin component. These sort of back scatterings lead to specific signature of skin components providing a high level of discrimination power for skin age identification [3]. The classification accuracy results which are 78% for our method and 57% for light based method proves that, our method has distinct advantage over the conventional "light based" ones. The more comprehensive data set (more sampling from broader age group and more attributes) will certainly improve our skin age model where the current statistical measures already indicate that laser based data is more stable than normal light based data. This is shown by the model parameters SSE_{Laser} = 3.827e-023 and SSE_{LED} = 7.07e-022 for our laser based and normal light based imaging respectively.

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 normal lights for skin aging analysis to support the similar works.

To the best of our knowledge, this successful pilot study is the first of its kind, and the method and low-cost equipment developed 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. Even though the best classification accuracy is obtained by use of two age groups, In future works more age groups would be used provided that a type of classifier (less sensitive to large number of classes) may be used. 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 by more accurate skin age models, which is expected to play a key role in personalized skin care.

References

[1] A.N. Rice, "Laser microscopy tests for skin damage," *Bio Photonics*, 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] Orun, A.B, E. Goodyer, H.Seker, G. Smith, V.Uslan And D. Chauhan, "Optimized parametric skin modelling for diagnosis of skin abnormalities by combining light back-scatter and laser speckle imaging", Skin Research and Technology, 2014; 1-13. doi:10.1111/srt.12142

[4] Seker, H., V. Uslan, A.B. Orun, E. Goodyer and G. Smith**, "**Prediction of skin ages by means of multi-spectral light sources", 36th Annual International IEEE EMBS Conference., Chicago 26-30 August, 2014 , USA.

[5] Orun, A.B., H.Seker, E.Goodyer, G.Smith and V.Uslan. " An improvement of skin aging assessment by non-invasive laser speckle effect: A comparative texture analysis". 2nd International Conference on Biomedical and Health Informatics, BHI2014, Valencia, Spain - 2014.

[6] 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.

[7] Nkengne1, A., R. Roure, A. B. Rossi and C. Bertin, The skin aging index: a new approach for documenting anti-aging products or procedures, Skin Research and Technology 2013; 19: 291–298.

[8] 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. **38** (2005) 2543–2555.

[9] Kyungrok, K., C. Young-Hwan and H. Eenjun. "Skin age estimation by using wrinkle features of skin", IEEE Conference on Multimedia and Expo 2009", ICME2009.

[10] Hayashi, J., H. Koshimizu and S. Hata. "Age and gender estimation based on facial image analysis", Proceedings KES2003 , pp.863-869.

[11] Phillips, D. 1995. Image Processing in C, Part 15 : Basic texture operations, C/C++ Users Journal, November 1995.

[12] Christoper, J.S. and T.A. Warner. 2002. Scale and texture in digital image classification, Photogrammetric Engineering & Remote Sensing, 68:1 , pp 51-63.

[13] Mahé, G.,P. Rousseau, S. Durand, S. Bricq, G. Leftheriotis, P.Abraham, "Laser speckle contrast imaging accurately measures blood flow over moving skin surface" , *Microvascular Research*, *Volume 81, Issue 2*, *March 2011*, *Pages 183-188*

[14] 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*, *Volume 84, Issue 1*, *July 2012*, *Pages 55-59*

[15] Briers, J.D 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., April 1996.

[16] Vapnik, V.N. "An overview of statistical learning theory", IEEE Transactions on Neural Networks, vol.10, no. 5, pp. 988 – 999, 1999.

[17] Scholkopf, B. and A. J. Smola, *Learning with Kernels: Support Vector Machines, Regularization, Optimization and Beyond*. MIT press, 2002.

[18] Chang, C and C.-J. Lin, "LIBSVM: a library for support vector machines", ACM Transactions on Intelligent Systems and Technology, 2:27:1--27:27, 2011.

[19] Orun, A.B and Aydin, N. "Variable optimisation of medical image data by the learning Bayesian Network reasoning", Proceedings of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'10), Buenos Aires, Argentina, 1st - 4th September, 2010.

[20] Celebiler, A. , 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**, (2013), pp: 2062-2078.