

# Image analysis of anti-aging parameters on specific facial areas after automated area-detection on high definition facial photographs

proderm GmbH, M. Seise, S. Bielfeldt, I. Kruse, K.-P. Wilhelm

# Introduction

The human face is a mirror of intrinsic and extrinsic skin aging. Cosmetic treatments are therefore focused to rejuvenate the view of the face by use of decorative cosmetics as well as skincare products. The impression of facial youth and attractiveness are the result of a complex process in the human brain . Nevertheless, an inner judgmental impression as the result of this process arises almost immediately in the consciousness of the observer<sup>1</sup>. Research revealed that visible irregularities of skin surface and pigmentation are key parameters forming the subjective impression of youth and beauty<sup>2</sup>. Image analysis on high definition facial photographs can objectively quantify such irregularities. As they appear in specific regions of the face, e.g. the sun exposed part of the cheek under the eye or the temple, individual detection and recovery of the correct test areas are crucial for reliable measurements.

### **Methods**

The proderm Image Analysis Software (PIAS) is an in-house developed software for interactive analysis of various image analysis parameters. It facilitates manual as well as automatic definitions of skin regions to be analyzed. Combined with facial imaging systems, like the proderm USRCIiP (Unit for Standardised Clinical Photography, proderm) or VISIA-CR (Canfield, USA) it allows for fully automatic region definitions. It uses a trainable algorithm for detecting facial keypoints like nose, eyes, mouth³. These keypoints are used to register pre-defined regions on the investigated face.



Image 1 Frontal & Side images before makeup application taken with USRCliP including automatically detected key points (pink) and automatically defined regions of cheek and forehead using PIAS (proderm Image Analysis Software)

### Experiment

To demonstrate the advantages of the automated recovery of facial test areas, the facial images of 6 female subjects, 35 years and older with visible pigmentation irregularities were investigated before and after a decorative treatment by a cosmetician. Frontal and side pictures were taken by USRCIIP. The subjects were acclimated at 22°C and 50% relative humidity for 20 minutes before taking baseline images between the makeup application and before final image acquisition. Pigmentation irregularities were evaluated using two different parameters for homogeneity:

(1) Global unevenness  $, {\rm H_{76^{\circ}}}$  is calculated as the standard deviation in CIELAB color space

where  $l_i$ ,  $a_i$ ,  $b_i$  are the CIELAB values for each pixel and

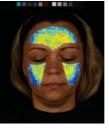
$$H_{76} = \frac{1}{N} \sum_{i=1...N} \sqrt{(l_i - \mu_l)^2 + (a_i - \mu_a)^2 + (b_i - \mu_b)^2}$$

 $\mu_{\mu}~\mu_{\alpha^{\prime}}~\mu_{b}$  are the average CIELAB values of the region of interest. Lower values are showing less inhomogeneity.

(2)  $H_b^{\text{ix}}$  as the local homogeneity parameter of CIELAB  $b^*$ . This parameter is calculated for every pixel as the inverse of the standard deviation of CIELAB  $b^*$  in a small sub-image realized by a moving window approach. The average value for each region of interest is reported. In this parameter higher values are showing higher homogeneity.

# **Results**

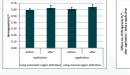


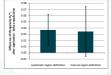


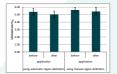


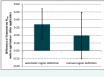
Images 2 - 3 Local homogeneity  $H_s^\infty$  before (left) and after makeup application (right) for subject #2. Red indicates regions of low values of  $H_s^\infty$ , thus low

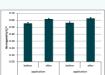
Images 4 - 5 Global unevenness  $H_{\chi_0}$  before (left) and after makeup application (right) for subject #2. Red indicates regions of high values of  $H_{\chi_0}$  thus low homogeneity.

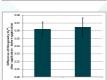


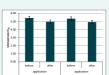


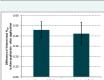












Graphs 1 - 4 The graphs are showing the local homogeneity H<sub>1</sub>" before and after makeup application for all subjects using manual and automatic region detection (I) and separately for subject!? (3). Further differences between H<sub>1</sub>" after makeup application and before application for all subjects (4) and separately for subject!? (2) are displayed. The errobars are showing 95% CL. The difference of H<sub>1</sub>" between before and after application images shows an improvement of the homogeneity after makeup application. The confidence intervals were smaller when using automatic region definition compared to manual definition.

For single subject evaluation, the difference in homogeneity can have a high variation, so that the results are not significant for manual definition of the region of interest, only for the automatic region definition.

Graphs 5 - 8: The graphs are showing the unevenness  $H_{16}$  before and after makeup application for all subjects using manual and automatic region detection (5) and separately for subject#7 (7). Further differences between  $H_{16}$  after makeup application and before application for all subjects (8) and separately for subject#7 (6) are displayed. The errorbars are showing 95% CI. The difference of  $H_{16}$  between before and after application images shows an improvement of the homogeneity after makeup application. The confidence intervals were smaller when using automatic region definition compared to manual definition.

For single subject evaluation, the difference in homogeneity after manual region detection can have an even higher variation compared to H $\mathbb{T}$ . The results are clarify different and not significant for manual definition of the region of interest, compared to the automatic region definition.

# Conclusion

Our work demonstrates how strongly test area variations can produce a bias, when investigating uneven skin pigmentation. We could show a reduction of this bias by using the automated definition of areas compared to manual area definition. The moving windows approach could reduce the bias even further.

A clear advantage of the automated software is the reduction of evaluation time as well as the avoidance of subjective influences on the results. Thanks to the automated landmark detection exact fusion of the images with overlay images of other sources (e.g. infrared imaging) is easy.

## References

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- 3. Davis E. King. Dlib-ml: A Machine Learning Toolkit. Journal of Machine Learning Research 10, pp. 1755-1758, 2005