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Exploiting Skin Melanin Network for Skin Pigmentation Classification

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Abstract

Accurate and precise classification/quantification of skin pigmentation is critical to address health inequities such as for example racial bias in pulse oximetry. Current skintone classification methods rely on measuring or estimating the color. These methods include a measurement device or subjective matching with skintone color scales. Robust detection of skin type and melanin index is challenging, as these methods require precise calibration. And recently acquired sun exposure may affect the measurements due to tanning or erythema.

The proposed system differentiates and quantifies skin type and melanin index by exploiting the variance in skin structures and skin pigmentation network across skin types. Our result with a small study shows skin structure patterns are a robust, color independent method for skin tone classification. A real-time system demo shows the practical viability of the method.

Introduction

Accurate and precise classification/quantification of skin pigmentation is critical to address health inequities such as for example racial bias in pulse oximetry [1]. FDA has also raised considerations about the impact of skin pigmentation in the accuracy of medical devices [2]. The method described in our paper proposes an objective method for skin pigmentation classification for these concerns. The method can also be applied in a broader context where skin tone measurement is required, such as phototherapeutic procedures (e.g. laser dermatological therapies, intense pulse light for hair removal).

This paper describes a method for classifying skin pigmentation using a deep neural network. The method exploits the variance in skin structures and skin pigmentation network across skin types. As such, it is not dependent on skin color. The system uses an optical setup consisting of an illuminator and a camera with a cross-polarizer to capture skin images. These images are then input to a deep neural network which outputs a melanin index or skin type. The network was trained using a dataset of skin images from 27 subjects with varying skin tones. The results of the study show that skin structure patterns provide a robust, color-independent method for skin tone classification. A patent covering this method was recently applied for under [3].

Related Work

Melanometry approaches can be broadly categorized into subjective and objective methods for assessing skin pigmentation [4].

Subjective methods rely on visual assessment or self-reporting:

- Fitzpatrick Skin Phototype (FSP): A six-category scale based on an individual's erythema sensitivity and tanning ability. While widely used, it lacks a standardized color palette and was originally designed as a questionnaire aiming to classify response to UV exposure rather than skin color.
- Race/Ethnicity Classification: Categorizing skin based on self-identified race or subjective evaluation of ethnic origin.
- Von Luschan's Chromatic Scale (VLS): Uses 36 opaque, colored glass tiles as a visual reference for skin color classification.
- And Munsell, Massey, Perla, LÓreal, Pantone SkinTone scale, and various other subjective skin tone scales: A color space used to classify skin tones.

These subjective methods have limitations, including inter-operator variability and potential inaccuracies due to mixed ethnicities or variations within ethnic groups [5].

Objective methods use optical devices to quantitatively measure skin pigmentation:

- Spectrophotometers: Measure light reflectance across the visible spectrum (350nm-750nm).
- Narrowband Reflectance Devices: Use specific wavelengths, often in the visible and near-infrared regions, to assess skin pigmentation.
- Tristimulus Colorimeters: Measure color values based on the CIE Lab* color space.

Objective methods for melanometry provide quantitative and objective measurements of skin pigmentation, allowing for continuous variable analysis rather than discrete categories. The current recommended objective standard is Individual Topology Angle (ITA) using these Colorimeters [5].

Our proposed objective method differs from these existing objective methods in several ways. Our method is not impacted ambient light, calibration for color space, light interactions on skin superficial disturbances and no clear sensitivity to tanning. Our method only exploits the presence of skin structure patterns to classify skin pigmentation.

Methodology

Our proposed objective method uses classification of skin structure patterns. The skin structure patterns are captured by an optical setup. A deep neural network is then used to classify the captured images of the skin structure patterns.

Skin structure pattern

In Figure 1 we show a schematic of a typical pigment network. This pigment network is captured by the optical setup. This pigment network consists of a grid of intersecting pigmented

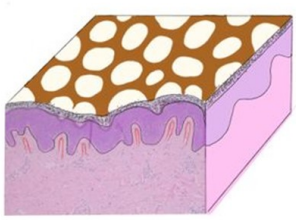

Figure 1. *Schematic of normal pigment network (to be updated)*

"lines" forming a pattern. The anatomic basis[6] of the pigment network is melanin in keratinocytes or in melanocytes along the dermal epidermal junction, representing the way the rete ridge pattern of the epidermis appears when viewed in the horizontal plane. The less-pigmented "holes" of the network correspond to tips of the dermal papillae and the overlying suprapapillary plates of the epidermis. A wide diameter of dermal papillae would correspond dermoscopically to wider network "holes," whereas narrow dermal papillae would result in a denser sieve of the grid. The pigment network may be less visible if the rete ridge pattern contains less melanin pigment.

Optical setup

The optical setup consists of an illuminator and a camera with a cross-polarizer. In Figure 2 shows the spectrum of the illuminator to observe skin structures. The camera is a standard RGB camera which images an area of approximately 5 by 5 millimeters.

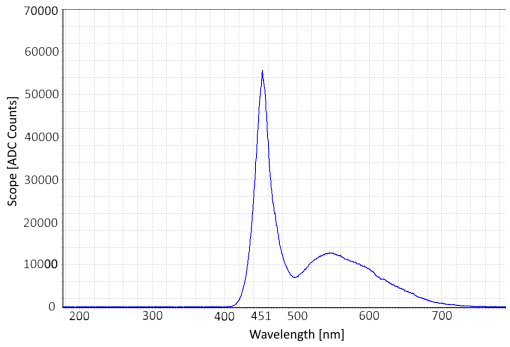

Figure 2. *Illumination spectrum to observe skin structure pattern*

In our experiments, we used a consumer skin camera (EH900U) to capture skin images.

Deep neural architecture for skin pigmentation classification

Input to the deep neural network are the images from the skin camera. In Figure 3 we show a sample of 4 different Fitzpatrick Skin Phototypes (FSP) [4].

The input images were normalized for color. Because of this normalization step, the trained network is then biased towards not learning about color differences in the skin images, but focusing on skin structures. In Figure 4 we show a sample of color-normalized images for 4 different Fitzpatrick Skin Phototypes (FSP) [4].

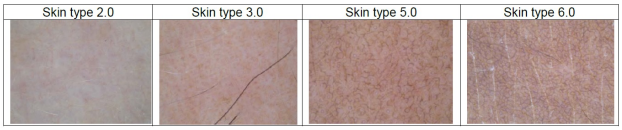

Figure 3. *Skin images for 4 different Fitzpatrick Skin Phototypes with skin structure patterns - 640x480 resolution of 0.5 cm diagonal of skin region*

Figure 4. *Color normalized skin images for 4 different Fitzpatrick Skin Phototypes with skin structure patterns - 224x224 cropped patch from captured images*

A deep neural network was developed to take input images skin and output a melanin index or skin type (FSP). The input image patch size is of 224 by 224 pixels. The architecture of the deep neural network was VGG16 [7]. It was trained as a regression problem with a mean squared error loss function.

Experiments

To train and validate our proposed objective method, we designed a study protocol. With this study protocol, we created a skin image dataset. The dataset was used for training and evaluation of the deep neural network.

Study Collection

We collected data on 27 healthy subjects [1] aged 18–65 years with varying skin tones.

Dataset

A dataset of 27 subjects was collected across 6 Fitzpatrick skin types to train and test the deep neural network. The dataset consists of answers to a short questionnaire and measurements from two devices.

The questionnaire classifies each subject for the Fitzpatrick Skin Phototype (FSP). The first device is the Mexameter MX18[8] that gives a melanin index as ground truth. The second device is the skin camera (EH900U) which captures skin image videos at a frame rate of 30fps. The videos were close-ups of the skin on the inner arm, outer arm, lower leg, and face cheek per subject. We captured images by recording with the close-up camera while moving slowly over the area on each body location per subject with a recording length of 30 seconds. For each video, for each body location, the camera was moved and held for around 30 spots. Each subject was recorded in two sessions, namely the pre-summer session and the post-summer session. This was to capture two different skin tanning levels. The total number of skin

[1]The study was approved by Philips Research' Internal Committee Biomedical Experiments, and all participants signed an informed consent form to agree to use their data for research and development purposes

images in this dataset is approximately 233,100 frames. Multiple skin patch regions of 224 by 224 pixels are taken from these skin images for training and inferencing. Figure 3 and Figure 4 shows an examples of this dataset.

Results

In the first experiment, data were split on different body locations for each subject. First set was used to train the neural network (train set). Second set was used to test the network (test set). The test set contains images from an unseen body location during training. The Figure 5 shows result of inferencing with the test set with this trained neural network. The horizontal axis is the expected skin type and vertical axis is the inferred skin type.

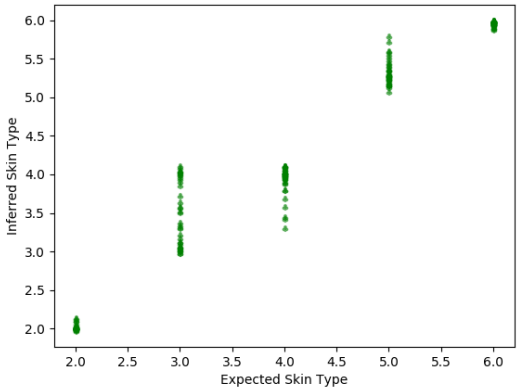

Figure 5. *Inferencing result for different skin types*

In the second experiment, to prove generalization of skin structure for melanin index (and skin type) classification across subjects, the dataset was split into folds for a cross-fold validation experiment. Each fold consists of a training set (of 24 subjects from 27 subjects) and a validation set (of 3 subjects from 27 subjects). These training and validation sets are mutually exclusive. The test set contains images from unseen subjects during training.

Figure 6, Figure 7 and Figure 8 show the results of the folds mentioned before. The horizontal axis is the expected melanin index and vertical axis is the inferred melanin index. As shown with each point in the figure, the trained network was able to differentiate and infer the melanin index with a minimal error spread.

System Demo

To show the practical viability of our proposed method, we have built a real-time system demo. In Figure 9 and Figure 10 show real-time inference of skin type 2 with melanin index of 107, and skin type 4 with melanin index of 296 respectively.

The real-time demo consists of 4 components: (1) EH900U camera (2) Raspberry Pi 2 Model B, (3) Intel Neural Compute Stick 2[9] and (4) display. EH900U camera streams live skin images to Raspberry Pi 2. Raspberry Pi 2 acts as a control processor and uses the Intel Neural Compute Stick. The described deep neural network has been deployed in the Intel Neural Compute Stick using Intel OpenVino [10] for real-time inference. Finally, the display shows the captured skin image together with inferencing skin type and inferencing melanin index.

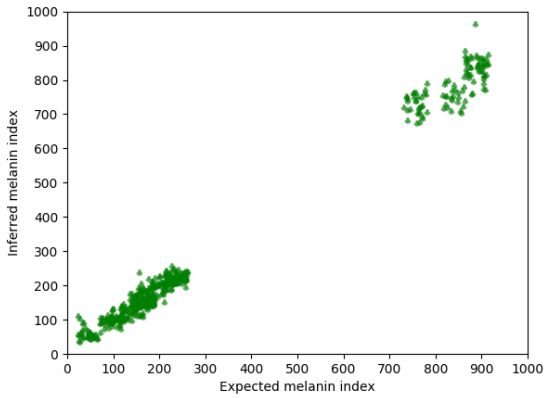

Figure 6. *Inferencing result for a training fold A*

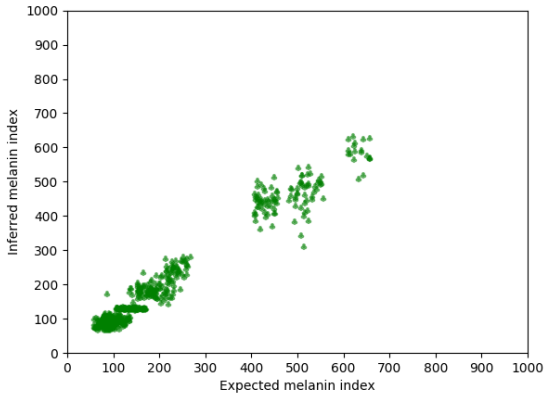

Figure 7. *Inferencing result for a training fold B*

Conclusions

This paper discusses a method that uses a deep neural network to classify skin pigmentation by exploiting color-independent skin structures. The network takes images from a skin camera as input and outputs a melanin index or skin type. The images are normalized for color, which biases the network towards learning about skin structures rather than color differences. The network was trained using a dataset of 27 subjects across 6 Fitzpatrick skin types. The dataset was split into training and validation sets for cross-fold validation. The results showed that the network was able to differentiate and infer the melanin index with minimal error. A real-time system demo was also built to show the practical viability of the method.

Acknowledgments

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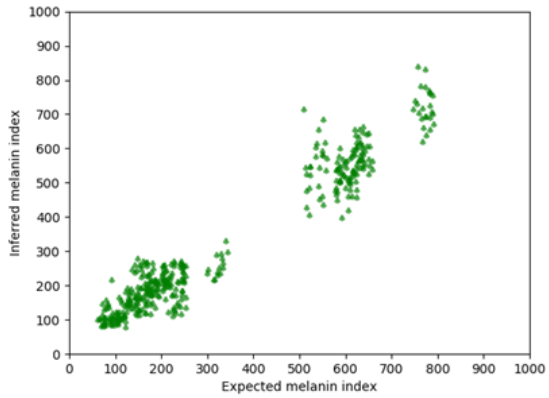

Figure 8. *Inferencing result for a training fold C*

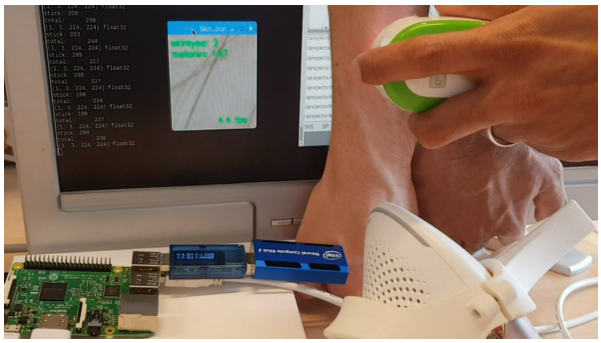

Figure 9. *Real-time demo of skin type 2 with melanin index of 107*

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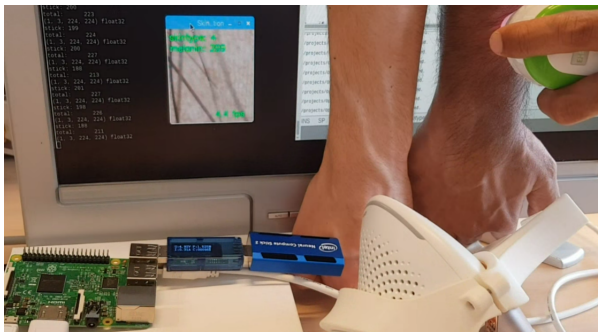

Figure 10. *Real-time demo of skin type 4 with melanin index of 296*

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Author Biography

Wim Verkruysse received MSc and PhD degrees in experimental physics and biomedical physics at the University of Amsterdam, Netherlands, in 1992 and 1998, respectively. Since 2010, Wim has worked at Philips Research, Eindhoven, on various topics including contactless pulse oximetry (measuring blood oxygenation with a camera) and evaluation of pigmentation measurement methods and skin color in general.

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