DERMA/care: An advanced image-processing mobile application for monitoring skin cancer

Alexandros Karargyris, PhD
National Library of Medicine,
National Institutes of Health
Bethesda, MD 20892, USA
akarargyris@gmail.com

Orestis Karargyris, MD
KAT University Hospital
Athens, Greece
okarargyris@gmail.com

Alexandros Pantelopoulos, PhD
West Wireless Health Institute
La Jolla, CA 92037, USA
alekospant@gmail.com

ABSTRACT
This paper describes a mobile hardware/software system (DERMA/care) to help with screening of skin cancer (melanomas). Our system uses an inexpensive apparatus (microscope) and a smartphone (iPhone). These two components standalone are sufficient to capture highly detailed images for use by experts with medical background. However the novelty of our system lies in the fact that we further improved the efficiency of the system by implementing an advanced image-processing framework to detect suspicious areas and help with skin cancer prevention. Our main goal was to demonstrate how smartphones could turn into powerful and intelligent machines and help large populations without expertise in low-resource settings.

Keywords
Mobile, health, microscope, image, machine learning, iPhone, iOS, melanomas, skin cancer prevention

1. INTRODUCTION
Over recent years, the mobile phone industry has been reshaped dramatically with the advent of new hardware and software technologies leading to sophisticated devices. These smartphones are equipped with fast processors, large memory and storage capacities that largely outperform NASA's Apollo 11 guidance computer (2KB memory and 1MHz processing power). Apart from this high performance, a variety of sensors and accessories accompany these devices allowing them to interact with the environment (i.e. high-resolution camera, GPS, wireless technologies, etc.). Finally, an advanced operating system (OS) sits on top of the hardware in charge of performing complicated tasks.

It is quite obvious and not unreasonable to say that smart phones are to Personal Computers (PCs) what PCs were to the mainframe computers back in the late 1970s. In a few years from now, cellphones, with their ever-increasing performance, will probably be the only essential machine for the average home user.

As of the beginning of 2012 there are two key players dominating the world mobile business: Apple Inc. and Google Inc. Although each one of them has a different business model, both of them offer high-level operating systems (OS): iOS and Android respectively. More importantly, both of them offer a Software Development Kit (SDK) that allows programmers to develop native applications. With a large collection of Application Programming Interfaces (APIs) programmers are able to access hardware capabilities and create various applications.

For this research we used a common smartphone, Apple's iPhone. We mounted an inexpensive microscope apparatus to capture highly focused images. We developed image-processing algorithms that take advantage of the smartphone's operating system and its underlying highly capable hardware. More importantly this application has the same capabilities with a medical image analysis program developed for the PC. Therefore, by developing this application we wanted and tried to showcase the many possibilities of this new technological era.

2. RELATED WORK
We conducted market research and as of March 2012 we were able to identify two mobile systems for skin cancer prevention: 1) Skin Scan by Cronian Labs [12] and 2) Handyscope by FotoFinder Systems GmbH [13]. While Skin Scan offers the ability to the user to capture screenshots using their iPhone and monitor the size of a suspicious case, Handyscope uses an expensive microscope apparatus (~500 Euros) that mounts to the iPhone to capture screenshots.

Our system's key contributions and advantages are synopsized in the following points:

1) An inexpensive microscope ($10-$20)
2) High zoom capabilities (60x)
3) Acquisition of physical dimensions of suspicious areas
4) An advanced image-processing framework with machine learning capabilities to help with prognosis
5) Ability to improve and update the decision support by having an anonymized database of skin cases

In the following paragraphs we describe our proposed system, DERMA/care. More specifically, in paragraph 3 an overview of the skin cancer risks and statistics from a medical perspective are given. In paragraph 4 a description of the image-processing framework is presented in detail. Paragraph 5 offers visual examples of results from the application. Finally this paper finishes with paragraph 6 in which conclusions, thoughts and future directions are given.

1082-3409/12 $26.00 © 2012 IEEE
DOI 10.1109/ICTAI.2012.180

3. SKIN CANCER - MELANOMAS

Melanoma is a cancer that develops from the malignant transformation of melanocytes. Those cells derive from the neural crest. Melanomas occur predominantly on the skin but they may arise in the gastrointestinal tract or brain. This type of skin cancer affects mostly adults (peak incidence in forth decade of life) and prevalence is equal for both sexes.

Melanoma is an increasingly important health issue, as more people are affected worldwide .It is estimated that its incidence is increasing by 6% every year. Recognition of the disease in early stages may lead to an early medical intervention, prior to any metastasis. Many efforts have been directed to public awareness campaigns.

62,480 new cases of melanoma occurred in the U.S. in 2008 with 8,420 deaths. Currently, in the U.S. approximately 1in 50 white patients, 1 in 200 Hispanic persons and 1 in 1,000 black persons develops melanoma at some point in his/her life [1].

Incidence of the disease varies worldwide. The highest rates are found in white populations in Australia, New Zealand, South Africa and the southern United States. However, Asian populations in China, Japan, Singapore and Hong Kong have the lowest rates. This demographic evidence suggests that there is a significant risk for white persons living in sunny areas of the world.

3.1 Etiology-Associated Risk Factors

-Personal traits: Blue eyes, fair hair, pale complexion, skin reaction to sunlight, freckles, high number of melanocytic nevi

-Positive family history: 2.2-fold higher risk for the development of melanoma

-Sun exposure over lifetime: UVA and UVB exposure; tanning beds [3]; number of blistering sunburns; low latitude (associated with increased sunlight)

-Atypical mole syndrome

3.2 Clinical presentation

The patient presents a skin lesion that has changes in size, color, contour, or configuration. The acronym "ABCDE" may be used to remember the physical characteristics suggestive of malignancy. ABCDE stands for: Asymmetry, Border irregularity, Color variations (especially red, white, blue tones in brown/black lesions), Diameter greater than 6mm, and Elevated surface. The lesion may bleed, ulcerate, itch or develop satellites.

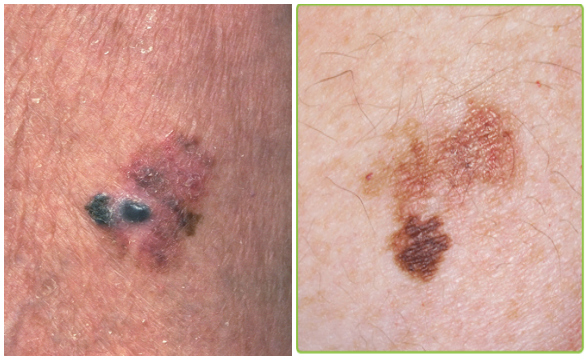

Figure 1. Malignant melanoma. Courtesy of Hon Pak, MD. Malignant melanoma, source: www.at-risc.org

Upon recognition of a suspicious lesion, a full thickness skin biopsy is performed in order to confirm diagnosis of melanoma.

3.3 Screening - Non-invasive technology

The benign pigmented lesions of the skin (nevi) are difficult to identify and differentiate from the early stage of malignant melanoma. Several studies have described diagnostic accuracy rates ranging from 50-75%. In the last decade dermoscopy has been introduced which opened new possibilities in the examination of pigmented skin lesions. A dermoscopy assessment involves the examination of a skin lesion under a specific optical system [4]. Simple analogue optical systems such as the dermatoscope (monocular vision) and more complex ones such as the stereomicroscope (binocular vision) provide direct visualization of the lesion and its distribution in the skin layers. The addition of a digital system has opened a new era of development with the advantages of computerized technology.

Figure 2. Digital epiluminescence microscopy equipment, Skin Cancer Unit, Centro Prevenzione Oncologica, Ravenna, Italy

The equipment used in dermatology centers/clinics nowadays can be highly specialized and expensive. It offers the possibility of mapping the skin lesions by means of digital photography, the archiving of those images and comparison of follow-up images of the same lesions.

With the popularization of technologies such mobile photography, a new possibility arises: A preliminary screening of the skin lesion by means of inexpensive mobile digital photography and algorithms based on the clinical ABCDE principles that are suggestive of malignancy.

4. MATERIALS & METHODOLOGY

DERMA/care system consists of two main components: i) an apparatus that mounts to the mobile phone, an iPhone 4/4S in our case, and ii) an image processing application to help achieve four (4) important goals:

a) Identifying suspicious areas in captured images
b) Analyzing these cases using image techniques
c) Classifying cases
d) Store cases for future review and comparison

In the following subsections the system is decomposed and presented in detail.

4.1 Platform

Apple's iOS offers a wide selection of functions to the developer through its SDK. Just for our application we had to use libraries to access: network connectivity, camera, local storage, graphics, email messaging, zip compression with encryption.

On top of that we additionally incorporated a library for developing our image-processing scheme. This library, Open Source Computer Vision – OpenCV [10], offers impressive image processing and computer vision capabilities. It is available as an open source, it was first developed by Intel Inc. in 1999, and it is now supported by Willow Garage Laboratory.

It is important for the reader to understand that OpenCV was first developed for personal computers and it was not until very recently (2011) that this library was ported for use in mobile operating systems like iOS and Android. Therefore, all the powerful and useful capabilities of OpenCV have been successfully transferred to such a small device like the iPhone making the mobile phone a replacement to the personal computer for being able to run on the fly the same image-processing functions offered on the computer.

Our project required significant zooming capabilities to be able to capture high-resolution images of the skin. Unfortunately the camera of a mobile phone like iPhone 4/4S does not feature high zooming. Therefore we had to look in the market for available accessories/apparatuses that could offer significant zoom. We were surprised to find a very inexpensive microscope that offered efficient zooming suitable for our application (see Figure 3). The average cost for this apparatus is only at the price range of $10-$20. This microscope can be easily mounted to the camera of the iPhone 4/4S. Additionally it offers lighting capabilities for better images. Its dimensions, including the mounting part, are very small (6cm x 4cm x 2cm).

Figure 3. a) Microscope with 60x zoom capability designed for the iPhone 4/4S. b) Microscope mounted on the iPhone while in use (LED light is on)

We were also stunned by the clarity of the captured images (see Figure 4).

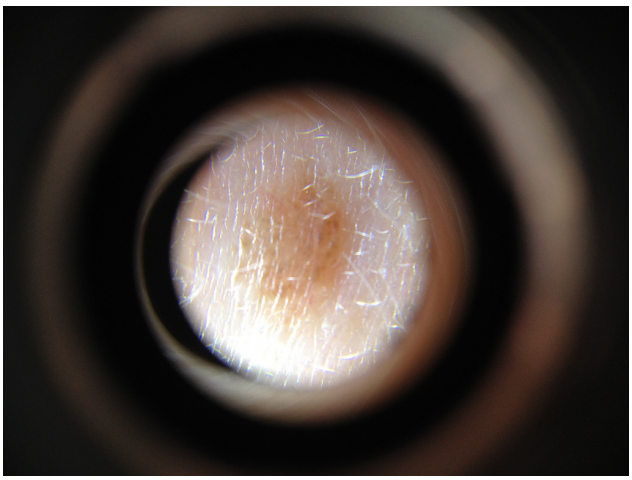

Figure 4. Image taken using the proposed microscope. This is a case of a non-malignant mole. The high detail of the skin can be easily identified (i.e. hairs are visible)

Our goal was to extract features from the acquired images that is meaningful and useful for the identification of the region-of-interest (ROI) or suspicious region. Our algorithm's flowchart is given below:

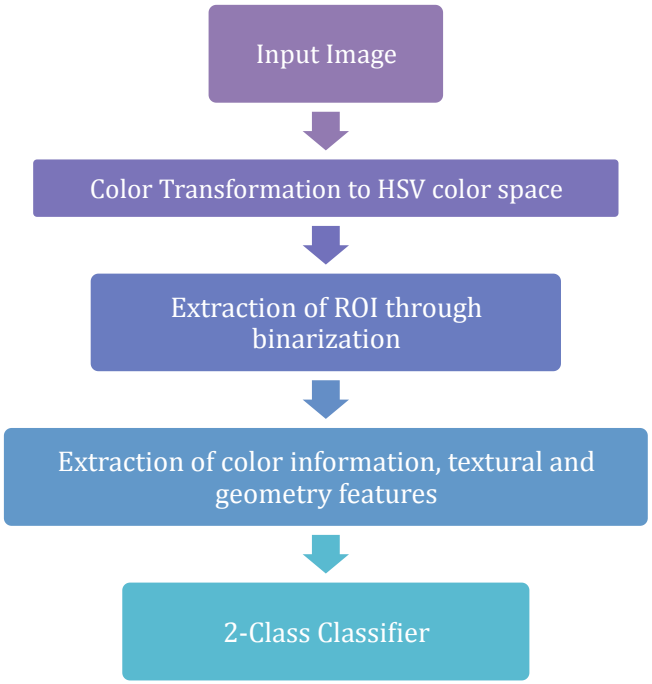

Figure 5. Flowchart of our image-processing algorithm

An important step to any image-processing application is the pre-processing stage. In this step the ROI needs to be identified and extracted from the rest of the image: the background. In a sense the image background works as a noise and therefore we need to pick the right approach that can more confidently separate the signal from the background.

In our case the preprocessing step consisted of:

a) "**Color Transformation**". The original image is captured from the iPhone's camera in the Red-Green-Blue (RGB) color-space. We know that the ROI usually is redder or browner than the rest of the skin (see figure 4) making it not unreasonable to propose of a cut-off threshold for the red component to detect the ROI. However a closer examination of the R channel shows that the whole image carries mixed values in the R channel making it impossible to find a threshold that can separate the ROI from the background skin with a minimum error. To overcome this issue we tried other color-spaces (see figure 6) that offer less uncorrelated color components. We were able to identify Hue Saturation Value (HSV) as a promising color-space. Hue channel proved to be more important than the rest of the other channels since it represents color and we also know that this is how human brain works to distinguish between objects [11].

b) "**Binarization**". We ran many experiments and trials to be able to identify a set of H-V threshold values that could binarize the HSV transformed image and extract the ROI properly. As mentioned before, a successful detection of the ROI with clear and proper boundaries is critical for the following steps: features extraction and final classification.

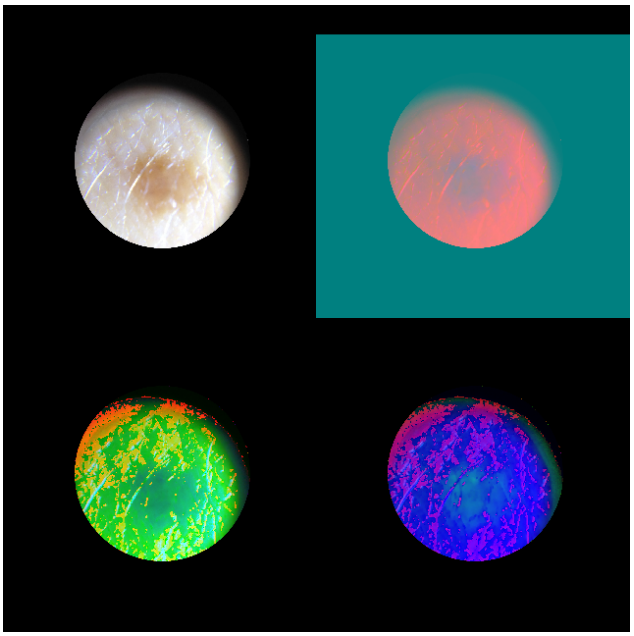

Figure 6. From left to right, clock-wise: a) Original RGB image captured with the microscope. ROI is browner/redder than the rest of the skin, b) Image transformed to LAB color-space, c) Image transformed to HSL color-space and finally d) Image transformed to HSV color-space. Please keep in mind that HSL and HSV color-space are almost identical [11].

4.2 Texture & Color Features

Texture is a very important characteristic of any natural image. In image processing there are two major categories of texture descriptors: a) pixel-neighborhood-based and b) frequency-based.

We used two of the common texture descriptors from both categories: Haralick's texture features [1] and Gabor wavelets [5] respectively.

Gray Level Coocurrence Matrix (GLCM) is a basis for calculating second order statistics measures. It is calculated over the image or ROI and each of its entries gives the probability that a pixel with value ***i*** is adjacent to a pixel of value ***j***. Haralick [1] extended this concept by calculating 14 moments: 1) angular second moment, 2) contrast, 3) correlation, 4) variance, 5) inverse difference moment, 6) sum average, 7) variance, 8) sum entropy, 9) entropy, 10) difference variance, 11) difference entropy, 12) measure of correlation 1, 13) measure of correlation 2, 14) local mean.

In our application we just used 4 of the common features: entropy, contrast, variance and angular second moment.

Gabor filters or Gabor wavelets have been widely used in image processing over the past two decades. In [6] Daugmann and in [7] Webster and De Valois showed that Gabor wavelet kernels have many common properties with mammalian visual cortical cells. These properties are orientation selectivity, spatial localization and spatial frequency characterization.

In this sense, Gabor filters offer the best simultaneous localization of spatial and frequency information [8]. Each wavelet of Gabor filters carries information about the energy at a specific frequency and a specific direction. When applied on an input signal like an image it is able to retrieve local features/energy of the signal. These local features contain a description of the image texture.

In mathematical terms, Gabor filters are defined in the following formulas **Error! Reference source not found.**:

$$\square\square,\square\ \square,\square,\square,\square,\ \square=\ \square-[\square-\square\ 2+(\square-\square)\ \ 2]2\square 2\ \sin(\square\ \square\cos\square-\square\ \sin\square+\square)$$

σ = Gaussian width

θ = orientation

W = frequency

φ = phase shift

X, Y = coordinates of the center of the filter

In our application, the original image of the ROI (I) is convolved with Gabor filter giving the Gabor transform (energy) of the image:

$$\square=\square\ *\square$$

After summing up across all the pixels of we measured the mean μ and standard deviation of the Gabor transformed ROI leading to a feature space. In our case we were interested in preserving a small amount of features so we used 4 scales and 6 orientations (24 total features).

4.3 Geometry Features

One of the big advantages of our system is the fact that the physical dimension of the area in view can be measured.

The reason is that when the system is in use the microscope has to come in contact with the user's skin before capturing an image (see figure 7a). Therefore we were able to easily measure the physical dimensions of the viewing area, which was a circle with 6.5cm in diameter (see figure 7b).

Having this knowledge the following important information for the ROI can be calculated:

a) Area size
b) Perimeter
c) Equivalent diameter

Our collaborating physicians really appreciated the ability to extract such information. Additionally, users are able to monitor changes in the shape and size of a specific case throughout a period time and if there are significant changes the system can have the ability to notify them on potential risk.

Using the perimeter and area size of the ROI the Shape Index (SI) is calculated using the formula:

SI is a measure of the roundness of the ROI. A perfect circle object has an SI equal to 1. All others shapes have SI>1. This is a quick but efficient feature of the irregularity of the ROI as mentioned in paragraph 3.

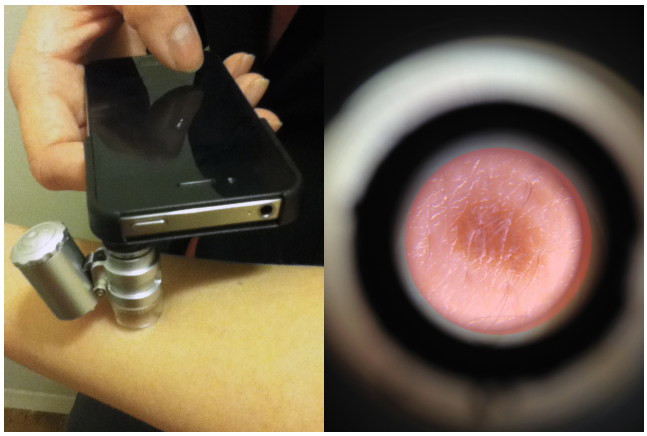

Figure 7. a) User places the microscope on their skin. b) Viewing area of the camera demonstrated here in red

4.4 Classification

For the classification process we used the built-in library of functions that OpenCV offers. As a classifier we used the reliable Support Vector Machines (SVMs).

Support Vector Machines (SVMs) are supervised learning methods widely used to classify data. The basic concept is that an SVM maps the input data to an n-dimensional space, where it tries to find the optimal hyper plane to separate the data sets [15]. The popularity of SVMs lies on their generalization ability for a wide range of pattern recognition problems. As well put by John Shawe-Taylor & Nello Cristianini: The key features of SVMs are: i) the use of kernels, ii) the absence of local minima, iii) the sparseness of the solution and iv) the capacity control obtained by optimizing the margin.

The process of SVM is shown in figure 8 below.

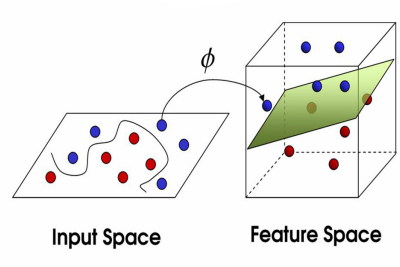

Figure 8. Mapping of the input space to the feature space. Optimal hyperspace is found for the 2-class problem. Source: Council of Scientific and Industrial Research

The optimal hyper plane that SVM finds is the one that will maximize is the margin between the support vectors. The vectors that define this margin are called support vectors and thus, the larger the margin is the smaller the generalization error of the classifier is.

In our case the vector of features we used derived from both categories: texture and geometry: 4 + 24 + 3 = 32 total features.

5. RESULTS

In collaboration with the dermatology department of hospital we retrieved six cases of suspicious cases. We also used six normal cases. We are in the process of retrieving more cases to enhance and test the algorithm. However acquiring cases requires effort and time since the medical personnel needs to be trained and consent of the patient needs to be given.

Our algorithm was able to successfully identify 5/6 of the normal cases as normal ones and 6/6 of the suspicious cases as abnormal ones.

In the following figures visual results are offered.

Figure 9. Screenshot of the application installed on an iPhone

Figure 10. Screenshot when opening the application. Instructions are given with graphics in four easy steps.

Figure 11. Screenshot with result after processing a suspicious case. The user is advised to follow up this case.

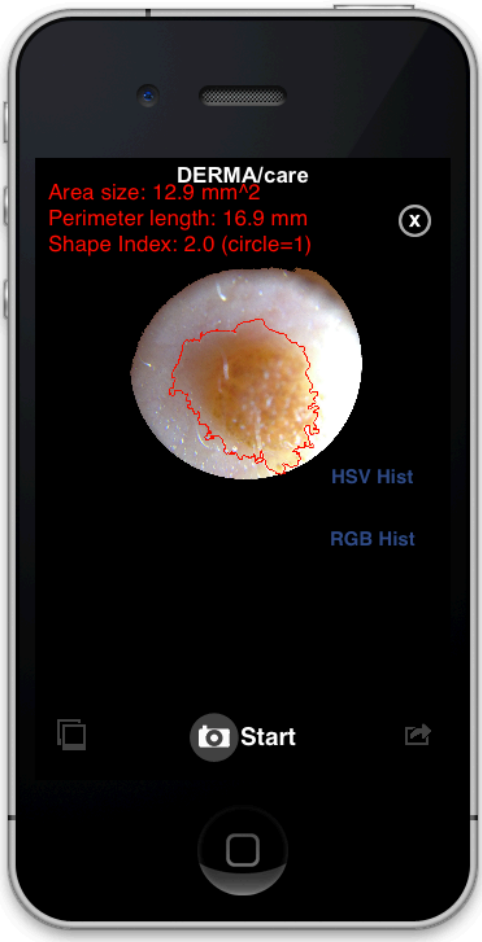

Figure 12. Screenshot of a case with the boundaries of ROI clearly marked in red. Additional information is given related to the physical dimensions of the ROI. This is important to the dermatologist [ref]. The user has the option to examine the histogram.

6. CONCLUSION & FUTURE WORK

In this paper we presented an application for skin prevention using a mobile device. The novelty of the system lies on the fact that an inexpensive accessory is used for improving the quality of the images. Additionally, an advanced software framework for image processing backs the system to analyze the input images. With this application we tried to emphasize and showcase the tremendous potentials new mobile technology offers.

Our system can be used either in low-resource settings by expertise personnel or in any environment by any mobile user. Also the low cost of our makes it ideal for outreach to a large population.

We are currently in the process of improving the classification part by increasing our training dataset. Additionally, we are planning to add encryption and security measures on top of the application to be fully HIPAA compliant [9]. We are also creating an online anonymized database where cases are publicly available for medical research or engineering development.

7. REFERENCES

[1] American Cancer Society. What Are the Key Statistic About Melanoma? Detailed Guide: Skin Cancer - Melanoma.

[2] Autier P, Dore JF, Eggermont AM, Coebergh JW. Epidemiological evidence that UVA radiation is involved in the genesis of cutaneous melanoma. Curr Opin Oncol. Dec 29 2010;Robert M. Haralick, ``Statistical and structural approaches to texture," Proc. IEEE, vol. 67, no. 5, pp. 786-804, 1979.

[3] Mogensen M, Jemec GB. The potential carcinogenic risk of tanning beds: clinical guidelines and patient safety advice. Cancer Manag Res. 2010;2:277-82.

[4] Argenziano G, Ferrara G, Francione S, Di Nola K, Martino A, Zalaudek I. Dermoscopy--the ultimate tool for melanoma diagnosis. Semin Cutan Med Surg. 2009 Sep;28(3):142-8.

[5] I. Fogel and D. Sagi. Gabor filters as texture discriminators. Biological Cybernetics, 61:103–113, 1989.

[6] J. Daugman. Uncertainty relation for resolution in space, spatial frequency and orientation optimized by twodimensional visual cortical filters. J. Opt. Soc. Am., 2(7):1160–1169, 1985.

[7] M. A. Webster and R. L. De Valois, "Relationship between spatial-frequency and orientation tuning of striate-cortex cells," J. Opt. Soc. Am. A 2, 1124-1132 (1985)

[8] What Are Log-Gabor Filters and Why Are They Good? - http://www.csse.uwa.edu.au/~pk/Research/MatlabFns/PhaseCongruency/Docs/convexpl.html Viewed in March 2012

[9] HIPAA Security Rule - http://www.hhs.gov/ocr/privacy/hipaa/administrative/securityrule/index.html (viewed in March 2012)

[10] OpenCV http://sourceforge.net/projects/opencvlibrary/

[11] http://en.wikipedia.org/wiki/HSL_and_HSV

[12] http://www.skinscanapp.com/about

[13] http://www.fotofinder.de/en/press/fotofinder-handyscope.html