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Automatic discrimination of actinic keratoses from clinical photographs

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ABSTRACT

Background and Objective: Actinic keratoses (AK) are common premalignant skin lesions that can progress to invasive skin squamous cell carcinoma (sSCC). The subtle accumulation of multiple AK in aging individuals increases the risk of sSCC development, and this underscores the need for efficient treatment and patient follow-up. Our objectives were to develop a method based on color texture analysis of standard clinical photographs for the discrimination of AK from healthy skin and subsequently to test the developed approach in the quantification of field-directed treatment interventions.

Methods: AK and healthy skin in clinical photographs of 22 patients were demarcated by experts and regions of interest (ROIs) of 50 × 50 pixels were cropped. The data set comprised 6010 and 13915 ROIs from AK and healthy skin, respectively. Color texture features were extracted using local binary patterns (LBP) or texton frequency histograms and evaluated employing a support vector machine (SVM) classifier. Classifier evaluation was performed using a leave-one-patient-out scheme in RGB, YIQ and CIE-Lab color spaces. The best configuration of the SVM model was tested using 157 AK and 216 healthy skin rectangular regions of arbitrary size. AK treatment outcome was evaluated in an additional group of eight patients with 32 skin lesions.

Results: The best configuration of the discrimination model was achieved by employing LBP color texture descriptors estimated from the Y and I components of the YIQ color space. The sensitivity and specificity of the SVM model were 80.1% and 81.1% at ROI level and 89.8% and 91.7% at region level, respectively. Based on the classifier results the quantitative AK reduction was 83.6%.

Conclusions: It is important that patients with AK seek evaluation for treatment to reduce the risk of disease progression. Efficient patient follow-up and treatment evaluation require cost-effective and easy to use approaches. The proposed SVM discrimination model based on LBP color texture analysis renders clinical photography a practical, widely available and cost-effective tool for the evaluation of AK burden and treatment efficacy.

1. Introduction

Actinic keratoses (AK) are common premalignant lesions of the skin, mostly affecting individuals of European ancestry [1] and constitute a significant workload in dermatology outpatient clinics worldwide [2]. AK result from chronic exposure to ambient ultraviolet radiation, thus they are mostly located on the chronically sun-exposed skin of older adults. With increasing age susceptible individuals develop multiple clinical and subclinical AK lesions that coexist in carcinogen-exposed skin areas ("field cancerization") [3]. The biological behavior of an individual AK may vary: it can remain relatively stable in form and size for a long period or spontaneously involute and ultimately disappear. On the other hand, some lesions may evolve into a hyperplastic, hyperkeratotic state and ultimately a minority of them (<0.1% of lesions/per year) may progress to skin squamous cell carcinoma (sSCC), a potentially lethal tumor [4,5]. However, since 60%–80% of sSCCs arise in AK fields, timely treatment of these lesions is anticipated to prevent progression [6–8].

In practice, and during the examination of a skin field, it is common for the clinician to document the presence of multiple, unevenly distributed, partly coalescent AK of different sizes. In these cases, evaluating disease burden at baseline and quantifying treatment efficacy is a challenging, real-life problem. The latter is highlighted in corresponding clinical studies where the use of subjective means to measure AK burden results in suboptimal interobserver agreement [9–11].

Research on computer vision systems for the evaluation of skin diseases is a continuously growing subfield of medical image analysis [12–14]. High-quality clinical images and specialized instruments that magnify deeper skin tissues have been coupled with automated detection

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systems to offer valuable computer-aided diagnostic tools for the assessment of keratinocytic skin malignancies. To date, non-invasive imaging of AK has addressed the identification and differential diagnosis of isolated skin lesions, employing techniques such as the cost-effective digital dermoscopy or the more sophisticated reflectance confocal microscopy (RCM) and high-definition optical coherence tomography (OCT). The diagnostic accuracy of OCT images has been assessed using ensemble classifiers and support vector machine (SVM) models in the differentiation of AK from basal cell carcinomas (BCC) [15]. Recently, the *in vivo* optical properties of facial AK subtypes and sSCC were quantified by high-definition OCT and a decision tree diagnostic algorithm for the discrimination of sun-damaged facial skin from AK subtypes and SCC was proposed [16]. Likewise, classification trees with morphologic RCM characteristics have been used for the discrimination of AK from normal skin [17] and to combine dermoscopic signs that predict the relevant histopathological findings in AK diagnosis [18]. Also, a Bayesian classifier and 3D features obtained by a sophisticated stereo image system have been used to automatically distinguish between keratinocytic malignancies [19]. In addition, rather cumbersome, non-portable equipment employing cross-polarized light and fluorescence has been proposed for skin cancer screening purposes, including the diagnosis of AK [20].

Conventional skin biopsy and histopathological examination remain the gold standard for confirming the diagnosis of AK. In general, most of the aforementioned non-invasive imaging approaches intend to substitute biopsy for the diagnosis of selected skin lesions [21]. However, regarding AK, the fundamental limitation of all aforementioned methods is that they are spatially elective, capable of supporting the recognition of few selected lesions per-patient and thus unsuitable for "field" quantification purposes. For example employing dermoscopy a relative small skin area can be evaluated per field of view (corresponding to approximately 4 cm^2 for a common commercially available digital dermatoscope; DermLite, PhotoSystem, 3Gen, LLC, Dana Point, CA, U.S.A.). Clinical photography on the other hand can provide morphological information of whole anatomic skin regions that in addition can harbor multiple AK, e.g. the skin of the face or the balding scalp, a quasi 'scanning modality' for morphological alterations of the skin surface.

The applicability of standard clinical photographs in the evaluation of keratinocytic premalignancies has been addressed in a limited number of studies. Using clinical photographs a hierarchical classification system based on the k-nearest neighbors (K-NN) model for discrimination between benign and malignant skin growths has been proposed [22]. Furthermore, automatic delineation of AK areas on clinical photographs has been elaborated using color space transforms and morphological features for erythema detection [23].

In this study, we developed an SVM model for discrimination of AK from normal skin, based on color texture analysis of non-standardized clinical photographs. Our aim was to use photography to quantify AK burden and to evaluate the outcome of treatment interventions that target skin cancerization fields. To the best of our knowledge, the present study is the first image analysis approach towards the quantification of AK burden for efficient treatment evaluation and patient follow-up by means of clinical photography.

2. Materials and methods

2.1. Acquisition of clinical photographs

Institutional approval was granted and patients with at least one biopsy-proven AK were recruited from a dermatology outpatients clinic; all patients gave informed consent for the photographic assessment of their skin lesions. A total of 30 patients (24 men) were included (mean age: 78 [range: 68–85] years). Photographs from 22 patients were used for the model development and the rest for evaluating AK burden reduction after treatment. Photographs were acquired using a Nikon D610 camera with a spatial resolution of 6016 × 4016 pixels. A 60 mm prime lens was adapted with two adjustable crossed polarized filters to minimize unwanted glare and a SIGMA EM-140 Macro ring flash. Images were rescaled to an equal final size of 50 pixels per millimeter employing as internal standards stickers attached to the skin (MACO Round Color Coding Labels, 0.635 cm [1/4 inch] in diameter, USA).

The same physician took all images at baseline and during follow-up visits with the volunteers seated. A detailed description of image acquisition is given in Fig. 1.

2.2. Discrimination model implementation

The automatic discrimination of facial AK lesions from healthy skin was addressed as a two-class classification problem, using the SVM classifier.

SVM is an advanced and extensively used classification method that has been successfully applied to a variety of real-world data analysis problems (text categorization, image recognition, bioinformatics and medical decision), mostly providing improved results compared with other techniques [24–26]. SVM is currently considered the standard method used to build a classifier from training data, especially in problems with continuous input features, as in our case. Further details on the SVM classifier can be found in Ref. [27].

In this study, the radial basis function (RBF) kernel was used for the SVM implementation. The SVM classifier performance depends on the choice of the parameter (C) which is also known as box constraint and the scaling factor (γ) which is the inverse width of the RBF kernel. We tested various pairs of (C, γ) values and we selected the one with the best predictive accuracy for both classes.

To train and validate the SVM classifier, AK and healthy skin 50 × 50 pixel regions of interest (ROIs) were cropped from areas demarcated by experts in each photograph (Fig. 2). A 50 × 50 pixel ROI is about one mm^2 and is the largest ROI adequate to sample the smallest demarcated by experts skin area. The data set comprised 6010 and 13915 ROIs of AK and healthy skin, respectively, extracted from 22 patients (Table 1).

Two different SVM models were constructed and evaluated. In the first model, each ROI is represented by its color local binary pattern (LBP) histogram (SVM_{LBP} model). In the second model, each ROI is represented by its texton frequency histogram ($SVM_{Textons}$ model).

Both SVM models were evaluated in terms of their sensitivity and specificity. For this, the number of true positives (TP), false negatives (FN), true negatives (TN) and false positives (FP) was obtained by each model. TN is the number of healthy skin ROIs correctly identified, FN is the number of AK ROIs incorrectly identified as healthy skin, TP is the number of AK ROIs correctly identified and FP is the number of healthy skin ROIs incorrectly identified as AK. Sensitivity is the probability that the SVM model will respond positively when tested on the AK ROI:

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \tag{1}$$

Specificity is the probability that the SVM model will respond negatively when tested on the healthy skin ROI:

$$\text{Specificity} = \frac{TN}{(TN + FP)} \tag{2}$$

Finally, the accuracy is defined as the probability that the SVM model will correctly classify both classes:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{3}$$

Evaluation of the discrimination models was performed using the leave-one-patient-out scheme, meaning that ROIs from all patients but one were used for the training and ROIs from the patient excluded for testing the model. To avoid overtraining the model in favor of the majority class (the healthy skin class), equal numbers of healthy skin and AK patterns were randomly selected from each patient in the training set.