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Classification of non-tumorous skin pigmentation disorders using voting based probabilistic linear discriminant analysis

Yunfeng Liang[a], Lei Sun[b], Wee Ser[c], Feng Lin[d], Steven Tien Guan Thng[e], Qiping Chen[e], Zhiping Lin[c,*]

[a] Interdisciplinary Graduate School, Nanyang Technological University, Singapore
[b] School of Information and Electronics, Beijing Institute of Technology, Beijing, PR China
[c] School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore
[d] School of Computer Science and Engineering, Nanyang Technological University, Singapore
[e] National Skin Centre, 1 Mandalay Road, Singapore

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ABSTRACT

Non-tumorous skin pigmentation disorders can have a huge negative emotional impact on patients. The correct diagnosis of these disorders is essential for proper treatments to be instituted. In this paper, we present a computerized method for classifying five non-tumorous skin pigmentation disorders (i.e., freckles, lentigines, Hori's nevus, melasma and nevus of Ota) based on probabilistic linear discriminant analysis (PLDA). To address the large within-class variance problem with pigmentation images, a voting based PLDA (V-PLDA) approach is proposed. The proposed V-PLDA method is tested on a dataset that contains 150 real-world images taken from patients. It is shown that the proposed V-PLDA method obtains significantly higher classification accuracy (4% or more with $p < 0.001$ in the analysis of variance (ANOVA) test) than the original PLDA method, as well as several state-of-the-art image classification methods. To the authors' best knowledge, this is the first study that focuses on the non-tumorous skin pigmentation image classification problem. Therefore, this paper could provide a benchmark for subsequent research on this topic. Additionally, the proposed V-PLDA method demonstrates promising performance in clinical applications related to skin pigmentation disorders.

1. Introduction

Over the past few decades, digital imaging techniques have been widely applied to assist the diagnosis of skin pigmentation disorders [1–3]. However, most studies focus on the detection and classification of skin tumors, such as melanoma [4,5] and pigmented basal cell carcinoma (BCC) [6,7]. While such studies are very important because skin tumors are likely to be cancers and threaten the health of the patients [8], some attention has recently been paid to developing computerized methods for the severity assessment of non-tumorous skin pigmentation disorders [9,10]. Non-tumorous skin conditions, such as melasma, lentigines, Hori's Nevus, and so on, mainly appear on the face and they are regarded as unsightly, causing much emotional stress to the sufferers [11]. Because non-tumorous skin pigmentation disorders are not fatal, many of these patients seek help from beauty salons and aestheticians instead of dermatologists. However, without the professional knowledge of skin pigmentation treatments [12,13], non-professionals may make a wrong diagnosis [14,15] and recommend options such as lasers and chemical peels, which could result in adverse effects on the patients [16]. With this background, the objective of this work is to provide the patients with a computerized tool that can easily and reliably diagnose non-tumorous skin pigmentation disorders based on their own facial image photographs. To the authors' best knowledge, this is the first study dealing with the non-tumorous skin pigmentation classification problem.

It is important to point out that diagnosis rules for non-tumorous skin pigmentation disorders differ greatly from those for their tumorous counterparts due to the appearance differences in their associated skin images. Tumorous conditions like melanoma, and BCC usually present as a distinct single lesion and a detailed image analysis of the lesion is carried out to look for specifics like size, shape, color, and structure. These prominent features are summarized to form some precise rules, for example, the ABCD rule [17,18], for skin tumor image classification. In contrast, the features of the non-tumorous skin pigmentation disorders usually affect the whole face and are bilateral. The pigmentation appearance varies a lot in terms of size, color and shape even for the ones in the same class. An example is illustrated in Fig. 1 for melasma, a common non-tumorous pigmentation. Due to the above-mentioned

* Corresponding author. School of Electrical and Electronic Engineering, Nanyang Technological University, 50 Nanyang Avenue, 639798, Singapore.
E-mail address: ezplin@ntu.edu.sg (Z. Lin).

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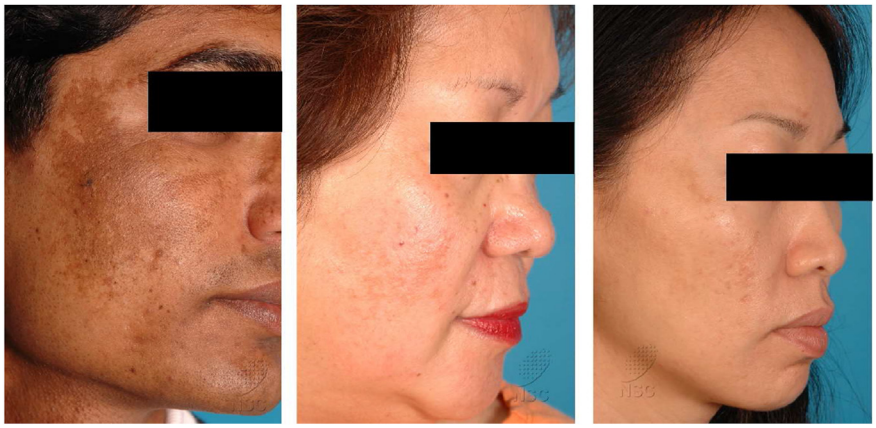

Fig. 1. Example images of melasma patients. The eyes are covered manually to protect privacy. It can be observed that the melasma pigmentation patches on each face make large difference in the appearance.

differences, methods specifically designed for the classification of tumorous pigmentation disorders may not be suitable for solving the classification problem of non-tumorous pigmentation disorders. Therefore, it is necessary to look for other more suitable image classification methods.

Many image classification methods have been developed in the past decades and they could potentially be used for non-tumorous skin image classification. These methods can be broadly classified into local and global approaches [19,20]. In the local approach, distinguished local patches in a given image are firstly marked by region detectors. The features are then extracted from these patches using different feature descriptors, such as scale invariant feature transform (SIFT) [21] and local binary patterns (LBP) [22], and so on, to represent the image and do the classification. While local methods could be used for skin image classification, the local region selection and description need to be carefully designed. For the real-world non-tumorous skin pigmentation image set that we have at hand, we observe that the classification accuracy is not high due to the large within-class variance in the image set.

An alternative to the local approach is the global approach, which uses the whole image as an input so that the local region detection process is not required [23,24]. To transform the high dimensional input image into a class label, the global methods project the data onto a suitable lower dimensional space. For example, the Fisher's linear discriminant analysis (LDA) based methods [23,25] project the input images onto a space with minimized within-class variance. Another well-known linear discriminant analysis model is the LDA incorporated with probability theory to form the probabilistic linear discriminant analysis (PLDA) model [26]. The PLDA is superior to the LDA since it models the categorical variances in images more accurately. However, one problem with some of these global methods, such as LDA and PLDA, is that they are more suitable for problems with small or moderate within-class variance because the image patterns need to be closely aligned [20]. To handle large within-class variance, PLDA is combined with a tied analysis (tied-PLDA) [27,28] so that the categorical (class) images are further divided into subclasses. This allows the large within-class variance of the whole class to be replaced by several smaller within-class variances with respect to the divided subclasses. It should be pointed out that the tied-PLDA model requires prior information in the training process to divide the data into subclasses. For example, in Ref. [27], the tied-PLDA model requires the pose angle of each image in the training procedure. However, in our non-tumorous skin pigmentation image set, no such prior knowledge is available, which may typically be the case with other skin pigmentation image sets.

In this paper, we propose an effective method for non-tumorous skin pigmentation classification, with an emphasis on tackling the large within-class variance problem. Specifically, a voting based PLDA (V-PLDA) method is developed by incorporating a voting scheme into an approximate PLDA method. We first show that for a dataset with large within-class variance, the original PLDA model could be approximated with an individual matching process. This is further enhanced via a voting scheme. The main advantage of the proposed V-PLDA method is that it excludes samples that have small joint probabilities with the testing sample while utilizing those samples that have large joint probabilities with the testing sample, which makes the final classification decision more robust.

The rest of the paper is organized as follows. In Section 2, the PLDA method is briefly reviewed. Section 3 discusses the problem of large within-class variance, the individual matching process, and the proposed V-PLDA method. Simulations are also carried out in this section to verify the effectiveness of the proposed V-PLDA method. Section 4 applies the proposed V-PLDA method to the real-world non-tumorous skin pigmentation image set and compares the results with both the original PLDA method and several state-of-the-art local and global-based image classification methods. Finally, conclusion is given in Section 5.

2. PLDA

Probabilistic linear discriminant analysis (PLDA) uses the generative model, which incorporates both within- and between-class variances. In PLDA, the input data are regarded as a linear combination of vectors associated with the within- and between-class covariances [28]:

$$\mathbf{x}_{ij} = \boldsymbol{\mu} + \mathbf{F}\mathbf{h}_i + \mathbf{G}\mathbf{w}_{ij} + \varepsilon_{ij}, \tag{1}$$

where $\mathbf{x}_{ij}$ is the jth data sample of the ith class, i and j are in the index sets of $[1,2, \ldots, I]$ and $[1,2, \ldots, J]$, respectively. $\boldsymbol{\mu}$ is the mean value of the whole training data. $\mathbf{F}$ and $\mathbf{G}$ denote two matrices whose columns are the basis vectors of the between-class covariance and within-class covariance, respectively. $\mathbf{h}_i$ and $\mathbf{w}_{ij}$ are the corresponding weights of the basis vectors. $\mathbf{h}_i$ represents the between-class character and the row elements remain the same for all the samples from the same class i. In contrast, $\mathbf{w}_{ij}$ represents the within-class character and the row elements change with not only the class label i but also the sample label j. ε_{ij} is a stochastic noise term with a diagonal covariance matrix $\boldsymbol{\Sigma}$. The assembled parameters $\{\boldsymbol{\mu}, \mathbf{F}, \mathbf{G}, \boldsymbol{\Sigma}\}$ are denoted as θ.

From model (1) and the assumption of Gaussian distributions of the hidden variables $\mathbf{h}_i$ and $\mathbf{w}_{ij}$ [28]: