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Pattern analysis of dermoscopic images based on Markov random fields

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ABSTRACT

In this paper a method for detecting different patterns in dermoscopic images is presented. In order to diagnose a possible skin cancer, physicians assess the lesion based on different rules. While the most famous one is the ABCD rule (asymmetry, border, colour, diameter), the new tendency in dermatology is to classify the lesion performing a pattern analysis. Due to the colour textured appearance of these patterns, this paper presents a novel method based on Markov random field (MRF) extended for colour images that classifies images representing different dermatologic patterns. First, each image plane in $L^*a^*b^*$ colour space is modelled as a MRF following a finite symmetric conditional model (FSCM). Coupling of colour components is taken into account by supposing that features of the MRF in the three colour planes follow a multivariate Normal distribution. Performance is analysed in different colour spaces. The best classification rate is 86% on average.

1. Introduction

In the last two decades, a rising incident of malignant melanoma has been observed. Because of the lack of adequate therapies for metastatic melanoma, the best treatment is still early diagnosis and prompt surgical excision of the primary cancer [1]. Dermoscopy (also known as epiluminescence microscopy) is an in vivo method that has been reported to be a useful tool for the early recognition of malignant melanoma [2]. Its use increases diagnostic accuracy between 5% and 30% over clinical visual inspection [3].

In order to give a diagnosis, physicians follow a two-step algorithm: (1) classify the lesion into melanocytic and non-melanocytic type and (2) for the melanocytic ones, classify into benign and malignant lesions. In order to perform the second step, four different approaches are the most commonly used: the ABCD rule of dermoscopy, the 7-point checklist, the Menzies method, and pattern analysis [4].

The currently available digital dermoscopic systems offer the possibility of computer storage and retrieval of dermoscopic images and patient. Some systems even offer the potential of computer assisted diagnosis (CAD) [5,6]. As diagnostic accuracy with dermoscopy has been shown to depend on the experience of the dermatologist, CAD systems will help less-experienced dermatologists.

Most of the technical papers developing methods to classify automatically dermatologic images are based on the ABCD rule (asymmetry, border irregularity, colour variegation, diameter greater than 6 mm or growing). Normally, the papers present one approach to cover one or some of the "letters" of the rule, that is, some are based on detecting asymmetry [7,8], borders [9–12], colour [13–15] or diameter [14]. There are some papers that cover the whole ABCD criterion. Tomatis et al. detect features for the ABCD rule, but they need a telespectrophotometric system [16]. Larabi et al. [17] extract some parameters to cover the ABCD rule, but they do not use it to classify the lesion but for retrieval. Maglogiannis et al. use a support vector machine to classify border features, colour features and texture features [18].

In any case, all the methods present in the literature, to the best of our knowledge, consist always of a feature extraction step (colour, texture and/or shape characteristics), an optional feature selection step and a final feature classification step. In general, the contribution of the papers is the election of new features to classify the lesion.

One of the novelties of this paper is that it is not based on detecting specific features in the images to cover the four letters of the ABCD rule, but it follows the new tendency in dermatology: to look for specific patterns in the lesions which will lead physicians to an assessment. Looking at the clinical references in this subject, we can see that the procedure can be summarized as a pattern recognition system. Physicians, in order to classify between benign and malign lesions, take into account the overall general appearance of colour, architectural order, symmetry of pattern and homogeneity (CASH). Benign melanocytic lesions tend to have few colours, architectural order, symmetry of pattern or homogeneity. Malignant melanoma often has many colours and much architectural disorder, asymmetry of pattern and heterogeneity [4].

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In this sense, the classification of the lesions can be summarized as follows:

(a) Reticular pattern or network pattern. It is the most common global feature in melanocytic lesions. It represents the junctional component of a melanocytic nevus.
(b) Globular pattern. It presents numerous "aggregated globules". It is commonly seen in a congenital nevus, superficial type.
(c) Cobblestone pattern. Very similar to the globular pattern but is composed of closer aggregated globules, angulated, resembling cobblestones.
(d) Homogeneous pattern. It appears as diffuse pigmentation, which might be brown, grey-blue, grey-black, or reddish black. No pigmented network is found. It is seen in the homogeneous blue nevi.
(e) Starburst pattern. It is characterized by the presence of streaks in a radial arrangement. It is commonly seen in Reed nevi or Spitz nevi.
(f) Parallel pattern. It is exclusively found on the palms and soles due to the particular anatomy of these areas.
(g) Multicomponent pattern. The combination of three or more distinctive dermoscopic structures within a given lesion is highly suggestive of melanoma.

An illustration of the patterns listed above is presented in Fig. 1.

In order to perform the pattern analysis procedure to classify the dermoscopic images we follow a model-based technique. In these methods, image classification is treated as an incomplete data problem, where the value of each pixel is known and the label, which designates the texture pattern the pixel belongs to, is missing. In such techniques, the image regions are modelled as random fields and the segmentation/classification problem is posed as a statistical optimization problem. It often provides more precise characterization of the image regions [19]. Most of the existing techniques use the spatial interaction models like Markov random field (MRF) or Gibbs random field (GRF) to model digital images. Stochastic model-based image segmentation/classification methods can be either supervised (model parameters obtained from training set) or un-supervised (model parameters have to be estimated from the observed image).

In our case, one important characteristic of texture patterns is colour. Panjwani et al. develop MRF models for unsupervised segmentation of textured colour images [20]. Each model is defined within each colour plane, taking into account interactions between the three planes. They work in the *RGB* colour space and perform a region splitting phase and an agglomerative clustering phase. Kato et al. [21] use a combination grey-level based texture features and colour instead of direct modelling of colour textures. The advantage is that most of the classical texture features can be used in their model. The colour features are calculated in the $L^*u^*v^*$ colour space. Tab et al. present a multiresolution colour image segmentation algorithm [22]. Regarding the MRF model for coloured textures, they assume conditional independence of the channels and they use the YUV colour space.

Regarding the use of MRF in segmentation of dermoscopic images not much appears in the literature. To the best of our knowledge, only Gao et al. [23] present something related. In their paper a comparison between different segmentation techniques is presented (principal component transform PCT/median cut algorithm, adaptive thresholding in PCT, k-means, MRF technique, etc.). The MRF technique is poorly explained, and they use the first plane of the PCT of the dermoscopic images, that is, is a grey-level version of MRF modelling. But, in any case, their purpose is to separate the lesion from the healthy skin, which is not our aim (we perform a classification of the different patterns that a lesion can present). In [14] the authors present a melanoma recognition system, but the use of MRF is not for the segmentation or characterization of the coloured patterns, but as a classifier (spin glass-MRF). Their inputs are features characterizing either the C letter of the ABCD rule or the D letter of the same rule.

In this paper a pattern recognition algorithm to detect different colour textured patterns is presented. New tendencies in dermatology, instead of applying rules such as the ABCD rule or the Menzies test, detect benign or malign lesions performing a pattern recognition step. In our case, instead of detecting features such as border irregularity, colours or some texture descriptors, we analyse the different coloured patterns that a skin lesion can present, i.e., globular pattern, reticular pattern, cobblestone pattern, homogeneous pattern and parallel pattern. To this purpose, an MRF model-based classification in the $L^*a^*b^*$ colour space is performed.

We devote Section 2 to explain the classification algorithm, Section 3 to present the results and Section 4 to expose the conclusions.

2. Model-based classification algorithm

For textured images, the theory based on MRF is an important field, which has been developed extensively in the last decades. MRF theory provides a convenient and consistent way for modelling context dependent entities such as image pixels and correlated features [24]. This is achieved through characterizing mutual influences among such entities using conditional MRF distributions.

In this paper we present a supervised method of classification. We are going to classify the following patterns: reticular, globular, cobblestone, homogeneous and parallel. A training set with images representing each pattern individually is available, and the problem to be solved consists in, when presenting a new image with a specific pattern, classifying it as the correct class it belongs to. It is not the purpose of this paper to separate the lesion from the normal skin, but the input to the algorithm will be a sample of the pattern of the lesion. Therefore, our database is formed by 40×40 colour images, each one representing one specific pattern.

In order to do that, we perform an MRF based texture modelling, where a texture is assumed to be an MRF. To model a texture is to specify the corresponding probabilities or Gibbs clique potential parameters. The following step is to classify the texture, which consists in the extraction of texture features and the design of a decision rule. In MRF modelling, texture features correspond to the MRF texture parameters and feature extraction is equivalent to parameter estimation [24]. In the supervised case, the estimation is performed using training data that will establish reference parameters.

2.1. Image model

Following Xia et al. modelling [25], an image is considered as a random field G, defined on a $W \times H$ rectangular lattice, where W and H represent the image dimensions (in our case $W=H=40$). The lattice is denoted by $S=\{(i,j) : 1 \leqslant i \leqslant W, 1 \leqslant j \leqslant H\}$, which is indexed by the coordinate (i,j). The colour values are represented by $G=\{G_s=g_s : s \in S\}$, where $s=(s_i,s_j)$ denotes a specific *site* and the random variable G_s represents a colour pixel in the $L^*a^*b^*$ colour space. An observed image $g=\{g_s : s \in S\}$ is an instance of G. It can be described by a finite symmetric conditional model (FSCM) [26] as follows:

$$g_s = \mu_s + \sum_{t \in \eta_g} \beta_{s,t}[(g_{s+t} - \mu_{s+t}) + (g_{s-t} - \mu_{s-t})] + e_s$$

where $\eta_g=\{(0,1),(1,0),(1,1),(-1,1)\}$ is the set of shift vectors corresponding to the second order neighbourhood system, μ_s is the mean of the pixels in a window centred in site s, $\{\beta_{s,t} : t \in \eta_g\}$ is the set of correlation coefficients associated with the set of translations from the central site and $\{e_s\}$ is a stationary Gaussian noise sequence with variance σ_s^2.