Global pattern classification in dermoscopic images based on modelling

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Abstract

In this paper a model-based method of classificationof global patterns in dermoscopic images is proposed. Global patterns identification is included in the pattern analysisframework, the melanoma diagnosis method most used amongdermatologists. The modelling is performed in two senses: first adermoscopic image is modelled by a finite symmetric conditionalMarkov model applied to colour space and the estimatedparameters of this model are treated as features. In turn, thedistribution of these features are supposed that follow a Gaussian mixturemodel along a lesion. The classification is carried out by an image retrieval approachwith different distance metrics.A 78.44% success rate in average is achieved when globular,homogeneous, and reticularare classified and a 72.91% success rate when the multicomponent pattern is added.

1.   Introduction

A non invasive technique to assist dermatologists in the diagnosis of melanoma is dermoscopy, which is an epiluminescencelightmicroscopy, that magnifies lesions and enables examination down to the dermoepidermal junction. There are four main diagnosis methods from dermoscopic images: ABCD rule, pattern analysis, Menzies method, and seven-point checklist.

Pattern analysis, considered as the classic approachfor diagnosis in dermoscopic images, was deemed superior to the other algorithms during the 2000 Consensus Net Meeting on Dermoscopy (CNMD) [1]. Currently, it is the method most commonly used for providing diagnostic accuracy for cutaneous melanoma.

Pattern analysis seeks to identify specific patterns, whichmaybe local or global. Themelanocytic lesions are identified by theirgeneral dermoscopic features, defining their global pattern, and by specific dermoscopic criteria that determine their local patterns.The local features representindividual or grouped characteristics that appear in the lesion.The global features are presented as arrangements of texturedpatterns covering most of the lesion. The main global patternsare: Reticular pattern, Globular pattern, Cobblestone pattern,Homogeneous pattern, Parallel pattern, Starburst pattern,and Multicomponent pattern.

The aim of this paper is the classification of an entire pigmentedlesion into Reticular pattern, Globular pattern, Homogeneouspattern orMulticomponent pattern by texture analysis. Globules are also predominant in the Cobblestone pattern, however they are larger and more closely aggregated than in Globular pattern, thus, in this paper Cobblestone is considered a special case of Globular pattern. The automatic detection of Parallel pattern does not have a significant interest for the clinical community because lesions with this patternare only located in palm or sole. Starburst pattern is characterizedby the presence of pigmented streaks at the edge of agiven lesion. As our objective is the texture analysis of an entirelesion, this type of lesion escapes from our study.

Numerous works have focused on the extraction of local patterns[2], however, when dealing with the detection and/or classificationof global patterns, a few methods have been publishedin the literature.Tanaka *et al.* [3] presented an extraction of 110texture features to classify a pattern into three categories: homogeneous,globular and reticular. Gola *et al.* [4] presented amethod based on edge detection,mathematical morphology, andcolour analysis to detect three global patterns (reticular, globular,and homogeneous), but based on the predominant localpattern identification: globules, pigment network, and blue pigmentation.Abbas *et al.* [5] extracted colour and texture features in orderto classify it into the seven global patterns. In a previous work[6], the classification into five types of global patterns (reticular, globular,cobblestone, homogeneous, and parallel), was performed by a Markovrandom field (MRF)-based texture modelling.Lately, Sadeghi *et al.* [7] modelled the texture with the jointprobability distribution of filter responses to detect five patterns.However, these works classify patches extracted from a lesioninstead of a whole lesion.

To the best of our knowledge only thework presented in [8] classifiesan entire lesion based on the model-basedapproach proposed in [6]. In Section 5 the method describedin [8] has been tested with the database used in this paper inorder to establish a comparison with the proposed methods.

In this work, we propose to identify the global pattern that alesion presents by modelling. First, an imageis modelled as an MRF in colour space to obtain texturefeatures. In turn, these texture features are supposed to follow a Gaussian mixture model. Different distance metricsbetween Gaussian mixture distributions are analyzed. A nearest neighbour algorithm basedon these distance metrics is then applied, assigning to the testimage the global pattern of the closest training image.This work has been published in [9] where aextended study is presented.

2. Markov random field model

Models based on MRFsassume that the intensity at each pixel in the image depends on the intensities of the neighbouring pixels and they have wide acceptance for solving texture analysis problems.

As suggested Xia *et al.* [10], in this paper a finite symmetricconditional Markov (FSCM) [11] model characterizes theobserved image to obtain texture features. TheMRF model is detailed as follows: an image is consideredas a random field, defined on a *WxH*rectangular lattice, which is indexed bythe coordinate*(i,j)* . The gray-scale values are represented by, where denotes a specificsite. However, in this work, as it was proposed in [6], the randomvariable represents a colour pixel in the color spaceinstead of gray-scale values with range [0 255]. Let an observedpatch be an instance of , defined in a squarecentre on each site . It can be described by a FSCM [11] as follows:

Where

 isthe set of shift vectors corresponding to the second-order neighbourhood system, is the mean of the color pixels in the patchcentred in site, is the set of correlation coefficientsassociated with the set of translations from every site ,and is a stationary Gaussian noise sequence with variance.

Based on this FSCMmodel, a texture feature vector is definedas: , where is the mean of the colour pixels of the patch under study, is the estimation of the noise variance, and the other four components, , are the estimation of the correlation coefficients. As these features are computed from the colour space, the feature vector is formed by 18 components:

The parameters of the FSCM model are estimated by theleast-squares estimation method proposed by Manjunath and Chellappa [12]. Consider a region (patch) containing a single texture. Let be the set of all the sites belonging to the patch under consideration and be the interior of the region of .

where is defined by .

3. Proposed classification method

First, lesion is automatically segmented using a edge based level set method proposed in [13], and later applied to pigmented lesions in [9].
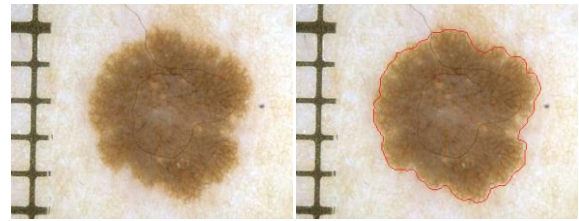

Figura 1.*Example of segmented image, using the method proposed in [13]*

In order to analyze a whole lesion, the lesion is divided intooverlapping patches. Patch size was fixed to 81x81. A displacementequal to nine rows or/and nine columns on the lesionis applied to obtain the next patch. Only the patcheswithout background or with a background area of up to 10% thepatch area are taken into account.

MRF features extracted from patches constituting a training lesion are supposed to follow a Gaussian mixture model:

where stands for the number of Gaussian kernels mixed,and are the mean vectors and the covariance matrices ofGaussian kernel and are the mixing weights. These parametersand weights are estimated iteratively from the inputMRF features using the expectation-maximization (EM) algorithm. In three different tests, data were modelled with 3,4, and 5 Gaussian kernels and, accordingly, the classificationmethod was applied. The best classification results were obtainedwith a three-component Gaussian mixture model.

Likewise, MRF features extracted from patches constituting a test lesion are supposed to follow a Gaussian mixture model:

The idea is to compare the Gaussian mixture model of a test lesion with the distributions corresponding to the training images. To this purpose different distance metrics between Gaussian mixture models are used: the symmetric Kullback–Leibler divergence [14], the Bhattacharyya-based distance metric [14], EMD [15] and a distance metric proposed by Sfikas *et al.* [14].

A nearest neighbour algorithm is applied and the test image is assigned to the pattern of the closest training image.
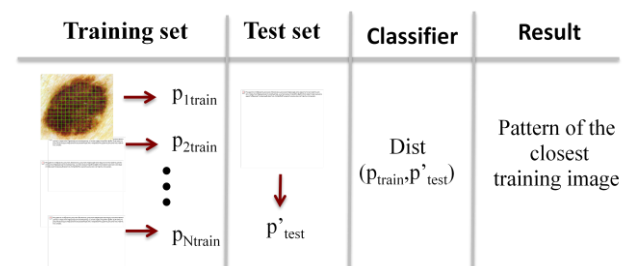
The procedure is show in Fig. 2.

Training set	Test set	Classifier	Result
p_{1train}			
p_{2train}		Dist (p_{train}, p'_{test})	Pattern of the closest training image
⋮	p'_{test}		
p_{Ntrain}			

Figura 2.*Procedure of lesion classification*

4. Image database

The image database used in this work is formed by 30 images, randomly chosen,of each type of pattern. Eight images of the 30 categorized as globular pattern, belong to Cobblestone pattern.

All images were extracted from the Interactive Atlas of Dermoscopy,published by Edra Medical Publishing New Media[16], which is a multimedia project for medical education withimages of pigmented skin lesions from different centres andhospitals. Some examples can be seen in Fig. 4.

It is important to note that each image presents an unique global pattern. This unique label does not mean that the lesion has an only local pattern, i.e., a lesion can show different local features although it is assigned to only one global pattern. Usually, a global pattern is determined by a predominant local pattern in a lesion.

5. Evaluation and results

To evaluate the performance of the proposed methods successclassification rate is computed. A 20-times three-fold cross validation is used. In Fig. 3, the classification success rate for each distance is presented.
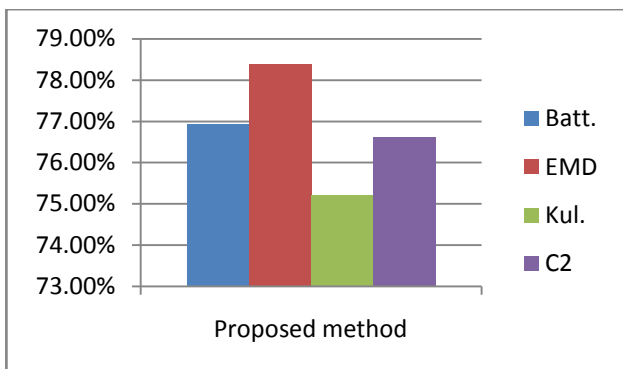

Figura 3.*Success classification rate of the method when different distances between Gaussian mixture distributions are used. Bhattacharyya-based (Batt.), EMD, Kullback–Leibler divergence (Kul.), and adistance proposed in [14] (C2)*

As it can been seen in Fig. 3, EMD is the distance metric which provides better results. Table 1 presents classification success rate obtained in the identification of globular, homogeneous and reticular pattern with this distance. Moreover, the proposed method in [8] has been included in the evaluation. The results show that the proposal has significantly better performance.

	Glob.	Homog.	Retic.	Average
Proposed	66.5 %	99.67%	69%	78.38%
method				
[8]	52.83%	74.83%	53.83%	60.50%

Tabla 1. *Classification results for the proposed method compared with the method proposed in [8]*

Once a successful global pattern classification has beenobtained, a further evaluation was performed. Thirty images of melanomas with multicomponent pattern were included in the study. The classification results into four categories are presented in Table 2.

Glob.	Homog.	Retic.	Multic.	Average
64.33%	95.83%	67%	64.5%	72.91%

Tabla 2. *Classification results when lesions with multicomponent pattern are included in the study*

The inclusion of this fourth pattern in the classification procedure reduces the success rate only by 5.53%. These promising results show the potential of this system for early melanoma diagnosis.

In both cases, the homogeneous pattern is identified with a success rate of over 95%, decreasing this rate for globular and reticular pattern identification. It is important to note that considering that the global pattern is determined by the dermatoscopic feature predominant in the lesion, its automated classification becomes hard due to the possible presence of different local patterns in the same lesion.Besides this intrinsic difficulty, the images from this Atlas of Dermoscopy present two difficulties for their automatic classification:intra-class variability, lesions belonging to the sameglobal pattern with very different appearance, and inter-classsimilarity, lesions belonging to different global patterns withcertain similar appearance.

6. Conclusion

In this paper, a classification method for global dermoscopic patterns has been proposed. The aim is to classify each lesion as a particular global pattern. This unique-label classification is motivated by the fact that a lesion is characterized by a global pattern and by one or more local patterns. The majority of the classification approaches in the literature are based on a feature extraction step followed by a classifier whose inputsare the features extracted. On the contrary, this paper proposes a technique based on modelling in different senses. First, an image is modelled by a MRF on the colour space. The estimated parameters of this model are treated as features. And then, these features within a
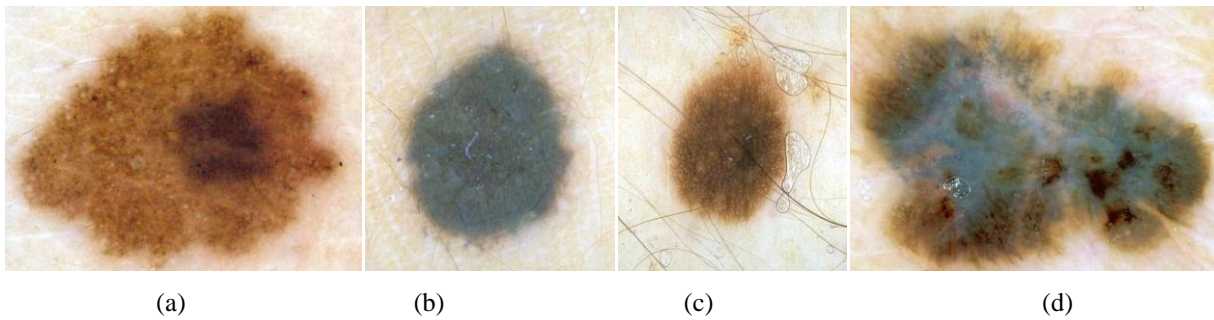
<div align="center">(a)   (b)   (c)   (d)</div>

Figura 4. *Examples of images from the database. (a) Globular pattern. (b) Homogeneous pattern. (c) Reticular pattern (d) Multicomponent pattern*

lesion are supposed to follow a Gaussian mixture distribution. The idea is to measure distances between these models and then to apply a nearest neighbour algorithm. The method obtained a 78.44% on average when globular, homogeneous and reticular pattern are indentified, a 72.91% when multicomponent pattern is included.

The main novelty presented in this paper is that MRF features within a lesion are modelled for classification purposes. Other authors [17], modelled pixel distributions as multivariate Gaussian distributions for segmentation tasks. Differently, in this paper features rather than pixel values are modelled, and models are applied to texture classification rather than for segmentation. Finally, it should be outlined that no previous attempts of global pattern model-based classification of full lesions can be found in the literature.

Acknowledgment

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