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Model-Based MRF Classification for Skin Lesions Using Global Pattern Method

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Abstract*:* In my project work, different model-based Markov Random Field (MRF) classification for skin lesions of global patterns in dermoscopic images are proposed. Global pattern method is used in the pattern analysis framework, diagnosis the melanoma used by dermatologists. A Dermoscopic image is modeled by a finite symmetric conditional Markov model and applied to L*a*b* color space and estimate the features. The input image is segmented by various techniques. This features are supposed to follow Gaussian model, Gaussian mixture model, and bag-of-features histogram model. The classification is carried out by an image retrieval approach with different distance metrics. The main aim of this paper is the classification of a entire pigmented lesion into Reticular pattern, Globular pattern, Homogeneous pattern by texture analysis.The image database extracted from a public Atlas of Dermoscopy. The best classification success rate is achieved by the Gaussian mixture model-based method with a 78.44% success rate in average.

Keywords: Markov Random Field (MRF), Gaussian Model, Gaussian Mixture Model, Bag of Features

I. INTRODUCTION

In the last two decades a rising incidence of malignant melanoma has been observed. Because of a lack of adequate therapies for metastatic melanoma, the best treatment currentlyis still early diagnosis and prompt surgical excision ofthe primary cancer Dermoscopy (also known asepiluminescence microscopy, dermatoscopy, and amplified surface microscopy) is an in vivo method, that has been reported to be a useful tool for the early recognition of malignant melanoma. There are various types of diagnosis methods from dermoscopic images: ABCD rule, pattern analysis, Menzies method, and seven-point checklist, three point checklist method. Pattern analysis, considered as the classic approach for diagnosis in dermoscopic images[1],which is automatically detect patterns in dermoscopic images of pigmented lesions. Pattern Analysis seeks to identify specific patterns, which may be global and local. It is the method most commonly used for providing diagnostic accuracy for cutaneous melanoma. It is a methodology first described by Pehamberger*et al.* [2], based on the analysis of more than 3000 pigmented skin lesions, and later revised by Argenziano*et al.* [3]. This defines the significant dermatoscopic patterns of pigmented skin lesions. Currently, it is the method most commonly used for providing diagnostic accuracy for cutaneous melanoma [4].

The main aim of this paper is the classification of a entire pigmented lesion into Reticular pattern, Globular pattern, or Homogeneous pattern by texture analysis. Pattern analysis allows to dermatologist not only the distinction between benign and malignant growth features but it also determines the type of a lesion.Tanaka*et al.* [5] presented an extraction of 110 texture features to classify a pattern into three categories: homogeneous, globular and reticular. Gola*et al.* [6] presented a method based on edge detection, mathematical morphology, and color analysis to detect three global patterns (reticular, globular, and homogeneous), but based on the predominant local pattern identification: globules, pigment network, and blue pigmentation. Abbas *et al.* [7] extracted color features from theCIECAM02 representation and texture features from steerable pyramids transform (SPT) from the dermoscopic image in order to classify it into the seven global patterns. In a previous work [8],we addressed the classification of global patterns following a model-based technique. We proposed a method to automatically classify five types of global patterns (reticular, globular, cobblestone, homogeneous, and parallel), in which a Markov random field (MRF)-based texture modeling was performed. In this work, we propose to identify the global pattern that a lesion presents by modeling in different ways. First, an image is modeled as an MRF in color space to obtain texture features. In turn, these texture features are supposed to follow different models: Gaussian model, Gaussian mixture model and a bag-of-visual words histogram model. Different distance metrics between Gaussian mixture distributions and between histograms are analyzed. A k-Nearest neighbor algorithm based on these distance metrics is then applied, assigning to the test image the global pattern of the closest training image. An image database extracted from the Interactive Atlas of Dermoscopy [3] is used for evaluation. The results of the proposed methods are compared with the method proposed in [9] with the same database.

II. SEGMENTATION

As the aim of the paper is the classification of a whole lesion into different types of global patterns, the first step is to isolate the lesion from the surrounding skin. The automatic nature of the segmentation process becomes crucial if the objective is the development of a computer-aided diagnosis (CAD) system. Therefore, an automatic segmentation algorithm is proposed. An edge based level set technique used in [10] is proposed as segmentation method. In this kind of methods, the basic idea is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred as the level set function. The challenge of a level-set algorithm is to make this function evolve so that its zero level converges at the real boundaries in the image.

A. Initial Contour

Level set methods are used to detect the boundaries of an image. The edge-based models fail to detect the boundaries when the initial contour is far from the desired object boundary. Thus, to overcome this limitation in the proposed method a relatively accurate initial contour is found.

The following steps are proposed to automatically find the initial contour.

1) First, the original image contains hair and grid marker

2) The image is smoothed with averaging filter for multidimensional images. Find the neighboring values.

3) Consider each pixel as a vector, principal component analysis (PCA) is applied to the image and the first component is retained.

4) Otsu'sthresholding method is applied to the first principal component image.

5) Contour of the dilated image is treated as the initial contour

6) Then the image is segmented by using level-set technique. Finally the segmented image is shown in (fig.6)

The artifacts are removed imposing shape conditions. As a lesion is supposed to approach a circle, the region of interest corresponds to the one with the biggest area and the lowest eccentricity. The eccentricity is defined as the ratio of the distance between the foci of the ellipse that has the same second-moments as the region and its major axis length. An ellipse whose eccentricity is 0 is actually a circle. The result of applying these two conditions is shown in Fig. 2(e).In most of the level set schemes, the curve evolution stops when a fixed number of iterations is reached. However, in this work, we propose a different stopping condition. When in two consecutive iterations the curve does not evolve the process is stopped, implying that it has reached an object boundary. Contour of an image is treated as a Initial Contour of an image. It is important to note that in spite of the presence of artifacts, such as hair and grid marker, a good segmentation is achieved in all cases.

III. CLASSIFICATION METHODS

In this section, the proposed model-based classification methods are detailed. The aim is the classification of a whole lesion, not only of a sample or patch of it. It is important to note that, in this paper, two different training sets of images are used, depending on the method implemented. Complete lesions compose the first dataset, whereas the second set is constituted by individual patches, each patch extracted from a different lesion of the first dataset. The extraction of these patches was performed randomly. The test set is constituted by complete lesions. None of the lesions included in the test dataset are included in the training dataset. In order to analyze a whole lesion, the lesion is divided into overlapping patches. Image should be taking as a fixed size. A displacement equal to nine rows or/and nine columns on the lesion is applied to obtain the next patch.

A. Gaussian Model

This approach is based on the assumption that the MRF features of the patches or samples constituting a test lesion follow a multivariate Gaussian distribution model. Different distance metrics are used in order to compare the multivariate Gaussian distributions of the test lesion and those from the training sets. Symmetric Kullback–Leibler distance Bhattacharyya distance and Frechet distance which is the closed form solution of the earth movers distance (EMD) in the case of two Gaussian distributions, are analyzed. The k-nearest neighbor algorithm (KNN) with the aforementioned distances has been applied for the final classification. In the first scenario, a test image is identified with the pattern closest to it. In the second case, a KNN approach is applied so that the test image is assigned to the class of the training image closest to it.

B. *Gaussian Mixture Model*

This model follows parametric probability density function models, such us Gaussian mixture models (GMM). In this approach MRF features extracted from patches constituting a test lesion are supposed to follow a Gaussian mixture model. This model represents a probability density function (PDF) as

$$p(f) = \sum_{j=1}^{k} N \pi_j (M_{j,} \Sigma_j)$$

where stands for the number of Gaussian kernels mixed,and are the mean vectors and the covariance matrices of Gaussian kernel and are the mixing weights. These parameters and weights are estimated iteratively from the input MRF features using the expectation-maximization (EM) algorithm.

C. *Bag Of Features Model*

The last approach is based on the representation of an image as a bag of features (BoF). This approach finds its origin, on the one hand, in the texture recognition by textons (basic elements of texture) and, on the other hand, in the bag of words scheme used for text categorization and text retrieval. The idea is to model an image as a frequency histogram of visual words (bag of features). These visual words are built from the quantification of descriptors (in our case the descriptors are MRF features) of local patches sampled from the training set. This quantification is usually carried out by a clustering algorithm such as k-means. The centroid of each cluster represents a visual word. The set of visual words forms a codebook.

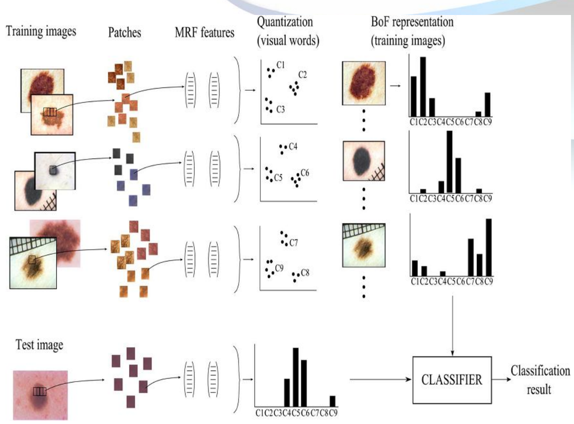

Fig.1 Bag of Features Approach

In Fig. 1 an overview of the proposed BoF approach to image classification is shown. In the classification step, overlapping patches are extracted from a new test image and a n-dimensional vector with MRF features is estimated from each patch. Each n-dimensional vector is assigned to the nearest centroid in the codebook, so that for each lesion a histogram of frequencies of clusters (bag of features) is formed. Finally, a classifier is applied to identify the training image whose histogram is closest to the one of the image to be classified. A KNN algorithm with different histogram dissimilarity measures is proposed as classifier. Finally, identify the type of skin lesions with levels.

The first novelty presented in this paper is that MRF features within a lesion are modeled for classification purposes. In other words, a multidimensional histogram is formed with the features within a lesion and this histogram is modeled with a particular density model. Then, classification is performed via comparison of histograms or density models, with specific dissimilarity functions. All images were extracted from the Interactive Atlas of Dermoscopy, for medical education with images of pigmented skin lesions from different centers and hospitals. The selected database includes both images with a clear diagnosis and images difficult to classify depending on the type of the lesion. Each image presents an unique global pattern. This uniquelabel does not mean that the lesion has an only local pattern,i.e., a lesion can show different local features although it is as signed to only one global pattern. Usually, a global pattern is determined by a predominant local pattern in a lesion.

III. Results And Discussion

The image database used in this work is formed by 30 images of each type of pattern, a total of 90 images. These 30 images from each global pattern were randomly chosen. It should be emphasized that some low quality images (blurry or low-contrast images) had to be replaced. To evaluate the performance of the proposed methods success classification rate is computed. Regarding the Bag of Features approach, the performance for the different histogram dissimilarity measures: EMD, statistic, histogram intersection (Hist.), Kolmogorov–Smirnov distance (Kol.), and Kullback–Leibler divergence (Kul.). They have been evaluated with different number of centroids or visual words. In view of the result it seems that the number of visual words does not significantly influence the success rate. However, distance using 20 centroids per class (60 visual words in total) achieved the best result.

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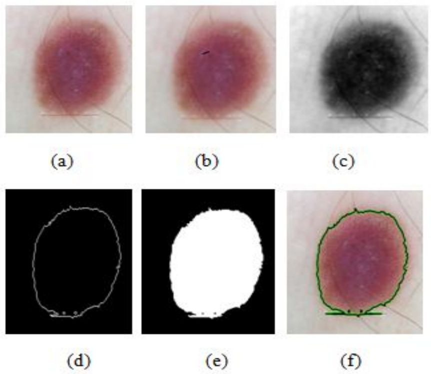

Fig.2 Segmentation Results (a) Original image with artifacts: hair and grid marker. (b) Smoothed image using an average filter. (c) First principal component image resulting of a PCA applied to the smoothed image(d) Otsu's thresholding to image (e)Contour of the dilated image is treated as the initial contour(f)Apply level-set technique to the dilated image.

The edge-based models fail to detect the boundaries when the initial contour is far from the desired object boundary. Thus, to overcome this limitation in the proposed method a relatively accurate initial contour is found. After the image is segmented, the segmented image is applied to the various technique such as Gaussian model, Gaussian Mixture Model and Bag-of Features Histogram Model. classification is performed via comparison of histograms or density models, with specific dissimilarity functions. All images were extracted from the Interactive Atlas of Dermoscopy, for medical education with images of pigmented skin lesions from different centers and hospitals. Then apply each model and get the results. Bag of features approach based on classification of an image. In this method patches are extracted from test image with MRF features are estimated from each patches. For each lesion a histogram of clusters (bag of features) is formed. A classifier is applied to identify the training image whose histogram is closest to the one of the image to be classified. In this method test image is compared with the database which consist of various training image. Finally applied the classifier and identify the type of skin lesions with levels

IV. Conclusion

In this paper, different classification methods for global dermoscopic patterns have 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 inputs are the features extracted. This paper proposes techniques based on modeling in different senses. First, an image is modeled by a MRF on the color space. The estimated parameters of this model are treated as features. And then, these features within a lesion are supposed to follow three different models. In the first one, it is supposed that a lesion follows a multivariate Gaussian distribution. The idea is to measure distances between Gaussian models (GM) and then to apply a KNN algorithm and k-means algorithm is suitable for finding the distance between object.

The same idea remains in the second approach proposed although a GMM assumption substitutes to GM. As in the previous case different distance metrics between GMMs are analyzed. Gaussian mixture model is a best classification model. The third model-based classification technique is a Bag of Features approach, where a image is modeled by a frequency histogram of visual words. In this case, different distances between histograms have been studied. The input image is segmented by level set technique. Then the segmented image is classified by using MRF model. Finally compare test image with training image and identify the type of skin lesions with levels. Compare the classification and get the classification success rate 78.44%, Gaussian mixture model is the best classification method to compare with another method such as Gaussian model.

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