Chapter 5
Combination of Color-Based Segmentation, Markov Random Fields and Multilayer Perceptron

Pedro Miguel Vieira, Nuno Renato Freitas, Carla Rolanda, and Carlos Santo Lima

5.1 Motivation

Angioectasias are lesions characterized by specific features, related to the color and shape. These lesions have a cherry red appearance, due to the nature of its origin (inflammation of blood vessels); and usually are characterized with a circular shape. As was previously reported, CIELab color has high efficiency in differentiating colors in an image (Connolly and Fleiss 1997). This color space is composed of three different channels: L represents the lightness information that goes from 0 (black) to 100 (diffuse white), and the components a and b represent the color-opponent dimensions. Negative values of channel a indicate green and positive indicate magenta (adequate for the detection of red color); and negative values of b indicate blue and positive indicate yellow (Weatherall and Coombs 1992). Since the red color in these lesions is easily spotted in the middle of the gastrointestinal tissue, CIELab was the chosen color space for processing the lesions. A pre-processing was included to overcome some problems with high values of the component a that do not represent a red area on the tissue. This step was designed by observation of a high number of images, leading to the understanding that certain areas of the images (usually near bubbles) could lead the segmentation step to fail. As was already shown in a previous work of the authors (Vieira et al. 2016), these types of lesions can be separated from the normal tissue by using probabilistic segmentation methods, as the Maximum A Posteriori (MAP) approach. This method was complemented with the use of Markov Random Fields (MRF) to improve the border definition. Because the segmentation

P. M. Vieira (✉) · N. R. Freitas · C. S. Lima
CMEMS-UMinho Research Unit, Campus de Azurém - Universidade do Minho, Guimarães, Portugal
e-mail: pmpvieira@gmail.com

C. Rolanda
ICVS/3Bs - PT Government Associate Laboratory, Braga/Guimarães, Portugal

Department of Gastroenterology, Hospital de Braga, Braga, Portugal

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used was based on probability approaches, the authors decided to use statistical features to characterize the tissue and consequently to classify the images as having angioectasia lesions or not.

5.2 Methodology

This method can be divided into three different subsections: Image Pre-Processing, Segmentation and finally Features Extraction + Classification.

5.2.1 Pre-processing

The pre-processing is made so the angioectasia lesions can be highlighted in the image when compared to the rest of the tissue. Due to the reddish appearance of angioectasias, the choice of color space was CIELab; in this specific space, high values of the component a represent the red color (Weatherall and Coombs 1992). Nevertheless, due to specific noise of WCE exams (e.g., bubbles), not only these lesions appear highlighted in the images. So, the following algorithm was applied to the images. Let C be an RGB image with a $M \times N$ size and D the corresponding image in CIELab color space. $C^k(i, j)$ and $D^l(i, j)$ represent the correspondent pixel in the component $k = R, G, B$ and $l = L, a, b$, respectively, and with the coordinates $i = 1, 2, \ldots, M$ and $j = 1, 2, \ldots, N$. In this algorithm (Algorithm 5.1), the pixels that present values of green or blue components lower than a chosen threshold (δ) are replaced by an average of a neighboring region (with a variable size) centered in that pixel ($\aleph\{D^l(i, j)\}$).

Algorithm 5.1 Pre-processing algorithm

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for each pixel (i, j) do
    if C^G(i, j) < δ or C^B(i, j) < δ then
        D^a(i, j) ← ℵ{D^a(i, j)}
        Break
    end if
end for
```

After this step, channel a of the images will have the regions with angioectasia highlighted. After this, the segmentation step will be applied.

5.2.2 Segmentation

The segmentation is based on a Maximum A Posteriori (MAP) approach by using the Expectation-Maximization (EM) algorithm (Vieira et al. 2016, 2019). A modified MRF, with a weighted boundary function, was included for spatial context modeling purposes.

The segmentation module uses a statistical classification based on Bayes rule. This rule indicates how the posterior probability of each class is calculated. MAP is computed for all classes and each pixel is assigned to the class with maximum MAP. Class conditional probability density function is usually assigned to the Gaussian function, being the observations modeled as a Gaussian mixture whose parameters can be iteratively estimated by using the EM algorithm.

The most appropriate parameters of the GMM are then estimated according to the Maximum Likelihood (ML) criterion (Zhang et al. 2001). Regarding the a priori probability, this has a precise meaning in the model regarding data partition over all classes; however, it is frequently used as a spatial regularizer by capturing neighboring information, not taken into consideration in the Gaussian mixture model that models pixel intensities as random variables which are independent and identically distributed. Neighborhood information can be modeled by Markov Random Fields (MRFs). MRF models have the ability of capturing neighborhood information to improve a priori probabilities $p(\omega)$. An image can be considered as a random field, or a collection of random variables ($\Omega = \Omega_1, \ldots, \Omega_N$) that are defined on the set S. Using Gibbs Random Field (GRF), the a priori class probability can be assigned such as

$$P(\omega) = \frac{1}{Z} \exp\left(\frac{-U(\omega)}{T}\right) \tag{5.1}$$

$$Z = \sum_{\omega} exp\left(-\frac{U(\omega)}{T}\right) \tag{5.2}$$

In this equation, the constant T represents the temperature and controls the level of peaking in the probability density, and the quantity Z is a normalizing constant which guarantees that $p(\omega)$ is always between zero and one. $U(\omega)$ is an energy function and is obtained by summing all functions $V(\omega)$ (clique potential) over all C possible cliques. A clique is defined as a grouping of pixels in a neighborhood system, such that the grouping includes pixels that are neighbors of another in the same system.

The Hammersley–Clifford theorem defines that if and only if a random field Ω on S is a MRF with respect to neighborhood system $\mathcal{N}$, then Ω is a GRF on S with respect to a neighborhood system $\mathcal{N}$. This fact allows to convert the conditional probability as a Markovianity condition of a MRF to the non-conditional probability of a Gibbs distribution of Eq. (5.1).

To compute the estimation of $p(\omega)$, the energy function used was based on Van Leemput et al. (1999):

$$U(\omega_j) = \sum_k \beta_k . l_{k,j} \tag{5.3}$$

In Eq. (5.3), k is the direction (in this case it can be horizontal or vertical) and $l_{k,j}$ is the Dirac impulse function in such a way that $U(\omega_j)$ depends on the count of pixels in neighborhood that do not belong to class j.

Usually, in practice, models are considered as isotropic, so the amount of variables to estimate is strongly decreased, becoming in this case β_k a constant. However, pixels near the borders are sometimes wrongly classified in the Gaussian Mixture especially due to the partial volume effect. Therefore, using the β_k parameter to model intensity differences in neighborhood pixels in order to reinforce border conditions has been used in several works where several functions have been suggested. The main idea is to set β_k in such a way that a direct interference on border location is achieved. Heuristically we want to avoid class j under situations of high variance that usually appear near borders, even if a large number of pixels belong to class j. Under relative smooth conditions the border can also be present and can be detected by pixel intensity variations which occur at corners of small structures. Some tests were conducted in order to compute β_k for pixels on and near the border of several angioectasias and the approximated function given by Eq. (5.4) was used as follows:

$$\beta_k = \frac{\sigma_k}{1 + \exp\left(-\sigma_k \frac{\sum_i^n |I_i - I_c| . \text{dist}(I_i, I_c)}{n}\right)} \tag{5.4}$$

In Eq. (5.4), β_k is dependent on the difference of intensities ($|I_i - I_c|$) of the neighbor in the direction k, but also of the distance between the pixel in the center and the neighboring pixel ($\text{dist}(I_i, I_c)$). The term σ is the standard deviation of the neighboring used in this case and presented in Fig. 5.1.

This energy function uses a 2D-neighboring system of 8 pixels that can be seen in Fig. 5.1, where the darker pixel is the current observation.

With all the previous steps followed, the process now is to find the best parameters. This is done in an iterative manner, proceeding as follows:

1. Initialization of parameters, which in this case was done by using K-means algorithm

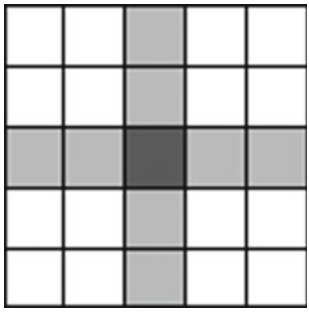

Fig. 5.1 Neighborhood system of 8 pixels used

2. E-step (expectation): calculation of likelihood of each sample for each class
3. M-step (maximization): find maximum likelihood value and recalculate the parameters

Steps 2 and 3 are repeated until convergence is achieved.

After the EM algorithm, a post-processing step was also included. This was done to improve the segmentation result since

1. isolated pixels are sometimes selected as abnormal region,
2. sharp and irregular edges appear in some lesions,
3. some pixels are included in the lesion class, but are in fact belonging to the normal class.

These problems are overcome with the following solutions:

1. Opening operation: using a small structuring element, the regions that consist of isolated pixels will disappear from the binary image.
2. Closing operation: using the same structuring element, smoothing the edges for both directions.
3. Shape analysis: because angioectasias are circular regions, connected components algorithm was applied, and lesions with a ratio between major and minor axis length superior than 3 were removed.

5.3 Feature Extraction + Classification

The output of the segmentation module described previously can have three different results:

1. after post-processing step, only one region exists in the image.
2. the image is divided into two different regions (one of them contains an angioectasia lesion),
3. the image is divided in two different regions (none of them contains an angioectasia lesion),

With situation 1, the image is classified as normal since no significant differences are found in channel a (so, different classes are not considered under the constraint of contiguous minimum area). When situation 2 or 3 happens, the classification module is necessary so the regions can be classified as normal or abnormal. This classification module needs features to feed it, that are extracted from both regions. This approach models the difference between both regions, in order to improve robustness against environmental conditions (related to device and subject changes). In fact, light characteristics may vary among different devices while tissue color may vary among different subjects.

Since the segmentation of the images was done based on the statistical distribution of the intensities, the features chosen were different statistical features that together

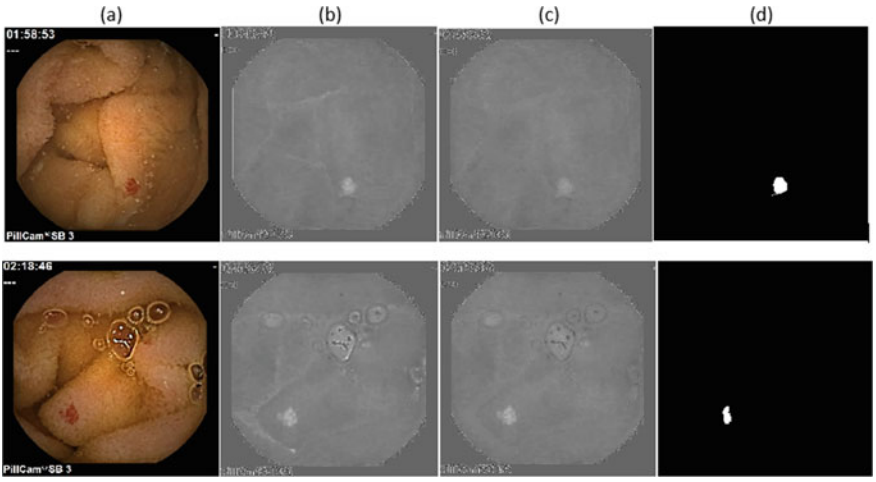

Fig. 5.2 Two examples of results with training images. **a** Original image. **b** Component a from CIELab. **c** Component a from CIELab after pre-processing step. **d** Segmentation result

can represent these distributions. In the current work, two different measures were computed (mean and variance), using the following expressions:

$$\mu = E\{X\} = \frac{1}{N}\sum_{i}^{N} x_i \tag{5.5}$$

$$\sigma^2 = E\{(X-\mu)^2\} = \frac{1}{N}\sum_{i}^{N} (x_i-\mu)^2 \tag{5.6}$$

All the features (from the different channels and different regions) were used as input to a Multilayer Perceptron (MLP) classifier with 1 hidden layer of 5 neurons. The output of the classifier is the presence or not of angioectasia tissue in each frame.

5.4 Results

Figure 5.2 shows some examples of results of the application of the proposed methodology over WCE images from GIANA 2017 dataset.

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