Chapter 8

Classification of squamous cell carcinoma based on color and textural features in microscopic images of esophagus tissues

8.1 Introduction

As more and more of today’s digital images are color images, color image segmentation and classification has become an important problem in image processing and analysis. Its applications include medical image analysis, face recognition, object based image and video coding, and hyperspectral image analysis. Object detection, segmentation, and classification are the key building blocks of a computer vision system for image analysis. The goal of detection and segmentation is to locate and extract meaningful objects from the image. For example, in cytological and histological images, this detection, segmentation, and classification play important roles in squamous cell carcinoma classification of diseased tissues.

Medical images are used as an important tool for determination of pathological condition of the vital organs of the body like lung, brain, esophagus etc. In this study, our focus is on microscopic images of esophagus tissue obtained from the abnormal regions of human esophagus detected through endoscopy. Segmentation is the first step towards automatic processing for analysis and evaluation of medical images. Image segmentation is the technique which partitions an image into units which are homogeneous with respect to one or more characteristics. Texture is one of the important

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characteristics used in identifying an object or a region of interest in an image. Robust segmentation results generally require the gray scale / color and textural information simultaneously. Texture features play an important role in image classification and analysis. In classification, texture features can be used to discriminate and label areas of an image, for example, crop identification in an aerial photograph and medical diagnosis of an X-ray photograph. Texture features can also be used in scene segmentation and identification in an image understanding or computer vision system, for example, in robot vision and industrial inspection. Therefore, the choice of texture features is the key in these applications [Zhenyong Lin and Attikiouzel 1989]. To diagnose and assess the behavior of many diseases, microscopic image analysis is important. This is a heavy and complicated work for the pathologists, both time consuming and expensive.

In this chapter, we present a novel method for feature extraction using color and textural information from microscopic images of esophagus tissues obtained from the abnormal regions of human esophagus detected through endoscopy. This method is used for classification of Squamous Cell Carcinoma (SCC) of esophagus, namely, poorly differentiated SCC, moderately differentiated SCC, and well differentiated SCC. Three different color spaces, namely, HSV, YCbCr, and Lab, are used for color texture analysis to test the classification of SCC of esophagus. The texture features are extracted from the luminance channel and the color features are extracted from the chrominance channels. The color and textural features are fused to generate feature vectors that characterize texture properties of image. In most cases of medical images of patients, the number of images available for training/ testing would be small. The proposed method is experimented for both small and large sample of training/ testing images.
8.2 Material and proposed method

8.2.1 Image data

The histological material used in this study has been collected from Gulbarga Diagnostic and Research Laboratory, Gulbarga. The image data set comprised 120 image samples from H and E (Haematoxylin and Eosin) stained tissue sections of esophagus. The digital images of stained tissue slides are captured by using a light microscopy imaging system (Olympus BX51 with DP12 camera) at a magnification of x40. For experimentation 120 color microscopic images of size 256x256 pixels are used.

8.2.2 Features

The proposed method, which is presented in the following, is based on the cooccurrence matrix and Haralick features that characterize color and texture of images. This method is classical in the pattern recognition community and have extensively been used on gray scale images. In the present approach, we extend this method to color texture analysis of images. We briefly recall the definitions: Let I be a grayscale image coded on m gray levels. Let \( s = (x, y) \) be the position of a pixel in I and \( t = (\Delta x, \Delta y) \) be a translation vector. The cooccurrence matrix \( M_i \) is a \( m \times m \) matrix whose \( (i, j)^{\text{th}} \) element is the number of pairs of pixels separated by the translation vector \( t \) that have the pair of gray levels \((i, j)\).

\[
M_i(i, j) = \text{card}\{(s, s + t) \in \mathbb{R}^2 | I(s) = i, I(s + t) = j\}
\]  

(8.1)

The choice of the relative position vector is the same as Haralick’s. This is a distance on one pixel in eight directions to take in to account the eight nearest neighbours of each pixel. The eight matrices obtained are then summed to obtain a rotation-invariant matrix \( M \). It is observed that since \( M_i(i, j) = M_{-i}(i, j) \),
M is symmetric. Haralick assumed that the texture information is contained in this matrix, and texture features are then calculated from it. He extracted 14 parameters from the cooccurrence matrix, but only five are commonly used because it was shown that the 14 are very correlated with each other, and that the five sufficed to give good results in a classification task [Vincent Arvis et al. 2004]. The features are homogeneity (E), contrast (C), correlation (Cor), entropy (H) and local homogeneity (LH).

\[ E = \sum_i \sum_j (M(i,j))^2, \quad (8.2) \]
\[ C = \sum_{k=0}^{m-1} k^2 \sum_{|i-j|=k} M(i,j), \quad (8.3) \]
\[ Cor = \frac{1}{\sigma_i \sigma_j} \sum_i \sum_j (i - \mu_i)(j - \mu_j)M(i,j), \quad (8.4) \]

where \( \mu_i \) and \( \sigma_i \) are the horizontal mean and variance and \( \mu_j \) and \( \sigma_j \) are the vertical statistics.

\[ H = \sum_i \sum_j M(i,j) \log(M(i,j)), \quad (8.5) \]
\[ LH = \sum_i \sum_j \frac{M(i,j)}{1 + (i-j)^2} \quad (8.6) \]

### 8.2.3 Fusion of color and texture features

The microscopic images of esophagus tissue samples are in RGB color space. The proposed method (Figure 8.1) consists of a change in the color space of the images, in order to obtain one channel containing the luminance information and two others containing chrominance information. Texture features are then computed from the luminance channel and other features, namely, color features are computed from the chrominance (intensity) channel.
On the intensity channel, Haralick features are extracted as described in section 3.2. The cooccurrence matrix is computed on images with different gray tones by uniform quantization. The aim of this is to obtain an indication of the loss of texture information due to a reduction of gray tones resolution. On the chromaticity channels, color features are extracted, consisting of the mean and standard deviation of each channel. Thus a total of 9 features characterize one image sample. The formula for mean and standard deviation are:

\[
\text{Mean}(m) = \frac{1}{N^2} \sum_{i,j=1}^{N} p(i,j)
\]  

\[
\text{Standard deviation}(sd) = \sqrt{\frac{1}{N^2} \sum_{i,j=1}^{N} [p(i,j) - m]^2}
\]

Firstly, the HSV (hue, saturation, value) color space is used. It corresponds better to how people experience color than the RGB color space does: hue (H) represents the wavelength of a color if it would be monochromatic. Hue varies from 0 to 1 when color goes from red to green then to blue and back to red. H is then defined modulo 1. as color is seldom monochromatic, saturation (S) represents the amount of white color mixed with the monochromatic color. Value (V) does not depend on the color, but represent the brightness. So H and S are chrominance and V is intensity. The transformation from RGB to HSV color space is described in the Chapter 1 (section 1.8.5).

Secondly, the YCbCr color space is used. This color space is widely used for digital video. In this format, luminance information is stored as a single component (Y), and chrominance information is stored as two color-difference components (C_b and C_r). The C_b represents the difference between the blue component and a reference value. The C_r represents the difference between the red component and a reference value. These features are defined for video processing purposes and so are not meaningful concerning human experience.
The transformation from RGB to \( YC_bC_r \) color space is described in the Chapter 1 (section 1.8.4).

Thirdly, Lab color space is used. The CIE Lab color space is based on a color vision model. This space is transformed from CIE Lab tri-stimulus values into an achromatic lightness values \( L^* \) and two chromatic values \( a^* \) and \( b^* \) using the transformation given in the Chapter 1 (section 1.8.6). The inherent properties of CIE Lab color space are that radial distance and angular position represent the chroma and hue of the color, respectively. It is much easier to handle color consistency and brightness in CIE Lab color space than in the other types of color spaces.

**Feature extraction algorithm**

Step 1: Input the RGB microscopic image \( I \) of esophagus tissue
Step 2: Transform the RGB color space of \( I \) to \( YC_bC_r \) / HSV / Lab and choose quantization level \( q \).
Step 3: Compute the cooccurrence matrix for luminance channel in the color space chosen in Step 2 and extract Haralick features (as described in Section 8.2.2)
Step 4: Extract the color textural features for chrominance channels (as described in Section 8.2.3)
Step 5: Fuse the color and Haralick textural features to yield a feature vector with 9 features (i.e. 5 Haralick features + 2 statistical moment features x 2 chrominance channels, as shown in Figure 8.1) and store in feature library
Step 6: Repeat Step 1 through Step 5 for all the training images and build the feature library completely.
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Original color image

Change in color space

Hue

Saturation

Value

4 Color features
Mean and standard deviation of Hue and Saturation channels

5 Haralick features
Homogeneity
Contrast
Correlation
Entropy
Local homogeneity

Cooccurrence matrix

Figure 8.1 Illustration of the fusion of color and texture features, in HSV, applied on well differentiated SCC.
8.3 Training and classification

For experimentation, the data set consists of 40 microscopic images of esophagus tissue obtained from the abnormal regions of human esophagus detected through endoscopy of each category namely, poorly differentiated, moderately differentiated, and well differentiated Squamous Cell Carcinoma (SCC) of size 256x256. The entire image is used for feature computation. Thus, the dataset contains 120 images.

8.3.1 Training

In the training phase, the color and texture features are extracted (as described in section 8.2) from t randomly selected sample images of each category, namely, poorly differentiated, moderately differentiated, and well differentiated SCC. These features are stored in the feature library, which are further used for classification of SCC images.

8.3.2 Classification

In the classification phase, the remaining 40-t images of each category (out of total 40 images of each category, t images of each category have been used for training) are used. The color and texture features are extracted for each test image as described in section 8.2 and then compared with the features of all the images from the feature library. The Canberra distance measure is used for computing the distance between image features. This distance measure allows the feature set to be in unnormalized form. The Canberra distance is given by

\[
\text{CanbDist}(x, y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|}
\]  

(8.9)

where x and y are the feature vectors of training and testing database, respectively, of dimension d.
The K nearest neighbors (K-NN) classifier is used for classification. In the K-NN classifier, the class of the test sample is decided by the majority class among the K nearest neighbors. A neighbor is deemed nearest if it has the smallest distance in the feature space. In order to avoid a tied vote, it is preferable to choose K to be an odd number. The experiments are performed choosing K=3, K=5, and K=7.

### 8.4 Experimental results

The experimentation has been done choosing a small training sample and also for a large training sample of images in different color spaces: YCbCr, HSV and Lab, with varying quantization levels. The experimental results of the proposed method are presented in Table 8.1 and Table 8.2, which show the percentage classifications for three different image classes, namely, poorly differentiated, moderately differentiated, and well differentiated SCC of esophagus tissue. Five sample images of each class are shown in Figure 8.2. The analysis of the experimental results shows that the classification accuracy of 100% is obtained using YCbCr color space.

<table>
<thead>
<tr>
<th>Value of k</th>
<th>Disease Class of SCC</th>
<th>Color Space</th>
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<tr>
<td></td>
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<td>YCbCr</td>
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<td>Quantization</td>
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<td>PD 100.00 100.00 100.00</td>
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PD: Poorly differentiated, MD: Moderately differentiated, and WD: Well differentiated
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Table 8.2 Classification results (in %) using proposed method with large training sample (30 training images and 10 test images of each class)

<table>
<thead>
<tr>
<th>Value of K</th>
<th>Disease Class of SCC</th>
<th>Color Space</th>
<th>YCbCr Quantization</th>
<th>HSV Quantization</th>
<th>Lab Quantization</th>
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</tbody>
</table>
PD: Poorly differentiated, MD: Moderately differentiated, and WD: Well differentiated

Small training sample:

The Table 8.1 shows that, for small training sample, the classification rate of 100% is achieved in all the three color spaces with varying quantization levels for poorly differentiated SCC. However, the overall classification rate is better in YCbCr color space than in other color spaces.

Large training sample:

The Table 8.2 shows that, for large training samples, the classification rate is 100% in all the three color spaces with varying quantization levels for all the three disease classes of SCC. However, only in case of well differentiated SCC, the classification rate is 80-90% in HSV and Lab spaces. But, in YCbCr space, the classification rate is 100% for all the three disease classes of SCC upto K=7 (except quantization level 128 at K=7).

Thus, in general, the classification rate of the proposed method is 100% in YCbCr space. Further, the proposed method is robust enough to yield classification rate of 100% even with small training/testing sample of images in case of poorly differentiated SCC in all the three color spaces. These results are significant in view of the fact that in most cases of medical images of patients, the number of images available for training/testing would be small.
Figure 8.2 Sample microscopic images of SCC of esophagus tissue: (a) Poorly differentiated, (b) Moderately differentiated, and (c) Well differentiated.
8.5 Summary

In this chapter, a novel method for feature extraction using color and texture of microscopic images of esophagus tissue obtained from the abnormal regions of human esophagus is presented. The proposed method consists of a change of the color space of the images, in order to obtain one channel containing the luminance information and two others containing chrominance information. Texture (Haralick) features are then computed from the luminance channel and other features, namely, statistical moment features are computed from the chrominance channels. This method is used for classification of SCC of esophagus namely, poorly differentiated SCC, moderately differentiated SCC, and well differentiated SCC. Three different color spaces, namely, HSV, YCbCr, and Lab are used for color texture analysis. The experimental results show that the good classification accuracy of 100% is obtained using YCbCr color space. The proposed method is robust enough to yield 100% classification rate even with small training/testing sample in case of poorly differentiated SCC in all the three color spaces. This is a significant result, since the number of training images is small in most cases and also the number of testing images of a patient may be small.