

# Advanced Image Analysis Tools Development for the Early Stage Bronchial Cancer Detection

P. Bountris, E. Farantatos, and N. Apostolou

**Abstract**—Autofluorescence (AF) bronchoscopy is an established method to detect dysplasia and carcinoma in situ (CIS). For this reason the “Sotiria” Hospital uses the Karl Storz D-light system. However, in early tumor stages the visualization is not that obvious. With the help of a PC, we analyzed the color images we captured by developing certain tools in Matlab®. We used statistical methods based on texture analysis, signal processing methods based on Gabor models and conversion algorithms between device-dependent color spaces. Our belief is that we reduced the error made by the naked eye. The tools we implemented improve the quality of patients' life.

**Keywords**—Bronchoscopy, digital image processing, lung cancer, texture analysis.

## I. INTRODUCTION

IN this paper we describe the work implemented at the “Sotiria” Hospital, in Athens Hellas concerning the early stage detection of lung cancer with the help of the Karl Storz endoscopy using white light (WL) and blue light (BL), and the digital image analysis through modern computer technology.

The endoscope device used in this hospital is the state-of-the-art in pneumonology. It is based on the autofluorescence phenomenon [1], [2]. The physicians have the opportunity to offer very early diagnosis and consequently early treatment and improved prognosis. However, distinguishing the normal from the abnormal or the suspicious tissue is not a trivial thing. No matter how good the endoscope system is and how good clinicians the physicians are, the diagnosis cannot be a 100% correct [3].

For image analysis processing we developed certain tools based on Matlab®. We analyzed both white light (WL) images and blue light (BL) images by using statistical methods of texture analysis (First Order Statistics), conversion algorithms between device dependent color spaces, and signal processing methods based on Gabor models.

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Now the physicians can study the bronchoscopy images in the privacy of their office and analyze them with the tools that we have developed.

Our aim is to develop advanced image analysis tools so that we can properly detect early stage dysplasia and carcinoma in situ (CIS), reducing the detection error made by the physicians' naked eye.

## II. METHODS

As a Biomedical Engineering Laboratory we tried to apply digital techniques to the images received by the bronchoscope analyzing them so that the physicians can make a much safer clinical diagnosis. We coupled the Karl Storz autofluorescence endoscope with an IBM PC using an Intel P-4 processor. The couple was made with the help of an S-Video cable in order to connect the PC with the bronchoscope [3]. The PC was retrieving video signal from the bronchoscope and with the help of video capturing software, we captured it. At the same time we took snapshots so that we could analyze them. The snapshots were taken under the instructions of the physician while the real patient was being examined.

### A. White Light Image Processing

The methods that we used for WL bronchoscopy image processing are the following:

#### 1) Texture Analysis by using First Order Statistics

The basic assumption is that different local textures in images can describe different physical characteristics corresponding to different objects. One of the most frequently used approach for texture analysis are First Order Statistics which are based on statistical properties of the gray level histogram of an image region [4]-[7]. The First Order Statistics that we used are shown in Table I [4].

Using the first texture analysis tool, the physicians can specify a region of the image and the program returns the values of the six texture features of Table I for the specific region. Under the instructions of the physicians we selected 3 healthy tissue regions and 3 suspicious ones in order to create a table of the values of texture characteristics (Table II). Fig. 2 depicts in blue squares the healthy tissue regions and in green squares the suspicious tissue regions that we selected.

The second tool of texture analysis offers the physician the ability to distinguish which regions of the image have similar texture characteristics with a small region that interests him.

As we observe from the Table II the suspected areas have low value of average gray level. This could be a criterion to determine all the suspicious areas of a bronchoscopy image. The physician can use the filter of the average gray level to find suspicious areas on the tissue by selecting on the image a small obvious problematic area. This tool works in 3 phases. The first phase is the image acquisition and its optimization by deblurring it. During the second phase the program requests from the physician to determine a small area in the image that has been classified as problematic or suspicious area (Fig. 3). For better results the physician can select more than one area, if he is really sure for their classification. In the third phase the program returns the same image overshadowed in all the areas that have similar value of average gray level. The

physician should pay attention to the overshadowed areas and analyze them very carefully. The same procedure can be followed by using the rest statistic measures of texture, e.g. entropy.

TABLE I  
FIRST ORDER STATISTICS

Texture Features	Expression	Measure of Texture
Average Gray Level	$f_1 = \sum_g gH(g)$	A measure of average intensity
Standard Deviation	$f_2 = \sqrt{\sum_g (g - f_1)^2 H(g)}$	A measure of average contrast
Smoothness	$f_3 = 1 - \frac{1}{(1 + f_2^2)}$	Measures the relative smoothness of the intensity in a region. $f_3$ is 0 for a region of constant intensity and approaches 1 for regions with large excursions in the values of its intensity levels.
Skewness	$f_4 = \sum_g (g - f_1)^3 H(g)$	Measures the skewness of an histogram. This measure is 0 for symmetric histograms, positive by histograms skewed to the right and negative for histograms skewed to the left.
Uniformity	$f_5 = \sum_g H^2(g)$	Measures uniformity. This measure is maximum when all gray levels are equal (maximal uniform) and decreases from there.
Entropy	$f_6 = -\sum_g H(g) \log_2 H(g)$	A measure of randomness

$g$  symbolizes the possible values of intensity and  $H(g)$  the percentage of pixels with intensity value  $g$ , respectively.



Fig. 1 Original image

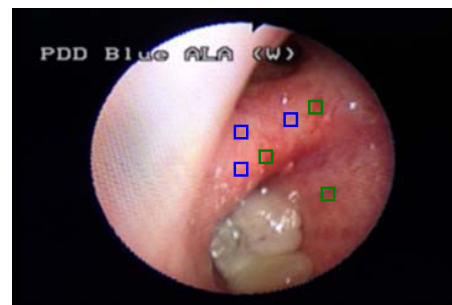


Fig. 2 Regions selection

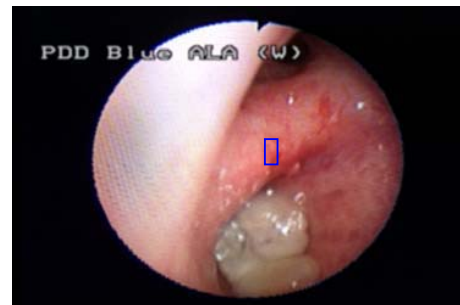


Fig. 3 Selection of a suspicious area

TABLE II  
FIRST TEXTURE ANALYSIS TOOL RESULTS

Regions	Average Gray Level	Standard Deviation	Smoothness	Skewness	Uniformity	Entropy
Suspicious tissue region 1	98.9135	6.1895	0.0006	0.0008	0.0469	4.5899
Suspicious tissue region 2	87.4074	3.4257	0.0002	0.0009	0.1126	3.4974
Suspicious tissue region 3	97.8750	6.6415	0.0007	0.0004	0.0470	4.5300
Healthy tissue region 1	156.6513	6.4018	0.0006	-0.0013	0.0482	4.5939
Healthy tissue region 2	168.9717	4.3814	0.0003	0.0000	0.0648	4.1191
Healthy tissue region 3	175.1627	4.7161	0.0003	-0.0000	0.0620	4.2358

## 2) Color Space Analysis

The color space analysis is based on the conversion from one color space to the other [4], [5]. Experimentally, we found that the best conversion is from the RGB space to the HSV space. The white color images we have are based on the RGB system. What we do is to turn the images to the HSV space. The HSV color space is formed by the H, S, and V components which stand for Hue, Saturation, and Value. In real world it is the system formed by people to select colors from a color wheel or palette. The HSV color space is formulated by looking at the RGB color cube along its gray axis, which results in the hexagonally shaped color palette. Hue is expressed as an angle around a color hexagon, typically using the red axis as the 0° axis. Value is measured along the axis of the cone. The V=0 end of the axis is black. The V=1 end of the axis is white, which lies in the center of the full color hexagon. Saturation is measured as the distance from the V axis. The HSV color system is based on cylindrical coordinates. Converting from RGB to HSV is simply a matter of developing the equations to map RGB values to cylindrical coordinates.

The hue is an angle from 0 to 360 degrees; typically 0 is red, 60 degrees yellow, 120 degrees green, 180 degrees cyan, 240 degrees blue, and 300 degrees magenta. Saturation typically ranges from 0 to 1 (sometimes 0 to 100%) and defines how grey the color is, 0 indicates grey and 1 is the pure primary color. Value is similar to luminance, except it also varies the color saturation. If the color space is represented by disks of varying lightness then the hue and saturation are the equivalent to polar coordinates (r, theta) of any point in the plane [4], [5].

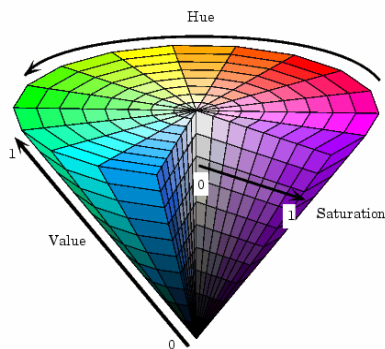


Fig. 4 The HSV color space

### B. Blue Light Image Processing

The advantage of autofluorescence bronchoscopy (blue light images) is that the autofluorescence emission spectra of the healthy tissue are different from the emission spectra of dysplasia and carcinoma in situ (CIS) [1], [2]. According to this fact we developed certain tools in order to specify different fluorescence intensities.

The methods that we used for BL bronchoscopy image processing are the following:

## 1) Texture Analysis by using First Order Statistics

Initially we tried to use the tools we developed for texture analysis on WL images, but after the experiments we proved that they were not effective. For this reason we constructed other tools (filters) to process the BL bronchoscopy images using first order statistics. Contrary to the texture analysis methods we applied on WL images, the texture features that showed to be effective on BL images were the smoothness, the entropy and the uniformity (Table I). We developed certain tools to analyze the above texture characteristics of BL images. Finally we managed to use these texture features in order to distinguish the suspicious regions, with autofluorescence emission different from the healthy tissue emission [3]-[7].

## 2) Gabor Filtering

Features related to the local spectrum have been proposed in the literature and used in one way or another for the purpose of texture classification and/or segmentation. In most of these studies the relation to the local spectrum is established through features which are obtained by filtering with a set of two-dimensional Gabor filters. Such a filter is linear and local and is characterized by a preferred orientation and a preferred spatial frequency. Roughly speaking, it acts as a local band-pass filter with certain optimal joint localization properties in both the spatial domain and the spatial frequency domain [8].

An input image  $I(x, y), x, y \in \Omega$  ( $\Omega$  the set of image points), is convolved with a two-dimensional Gabor function  $g(x, y), x, y \in \Omega$  to obtain a Gabor feature image  $r(x, y)$  as follows:

$$r(x, y) = \iint_{\Omega} I(\xi, \eta) g(x - \xi, y - \eta) d\xi d\eta \quad (1)$$

We use the following family of Gabor functions:

$$g_{\lambda, \Theta, \phi}(x, y) = e^{-\frac{(x'^2 + \gamma^2 y'^2)}{2\sigma^2}} \cos(2\pi \frac{x'}{\lambda} + \phi) \quad (2)$$

$$x' = x \cos \Theta + y \sin \Theta$$

$$y' = -x \sin \Theta + y \cos \Theta$$

The standard deviation  $\sigma$  of the Gaussian factor determines the effective size of the surrounding of a pixel in which weighted summation takes place. The eccentricity of the Gaussian and herewith the eccentricity of the convolution Kernel  $g$  determined by the parameter  $\gamma$ , called the spatial aspect ratio. The value  $\gamma=0.5$  is used in our experiments. Since this value is constant, the parameter  $\gamma$  is not used to index a Gabor filter in the following. The parameter  $\lambda$  is the wavelength and  $1/\lambda$  the spatial frequency of the harmonic

factor  $\cos(2\pi \frac{x'}{\lambda} + \varphi)$ . Since the spatial frequency tuning curve of a filter with an impulse response  $g$  has a maximum at  $1/\lambda$ , we refer to  $1/\lambda$  as the preferred spatial frequency of the Gabor filter. The ratio  $\sigma/\lambda$  determines the spatial frequency bandwidth of the Gabor filters (Fig. 5). The half response spatial frequency bandwidth  $b$  (in octaves) and the ratio  $\sigma/\lambda$  are related as follows:

$$b = \log_2 \frac{\frac{\sigma}{\lambda} \pi + \sqrt{\frac{\ln 2}{2}}}{\frac{\sigma}{\lambda} \pi - \sqrt{\frac{\ln 2}{2}}} \quad (3)$$

$$\frac{\sigma}{\lambda} = \frac{1}{\pi} \sqrt{\frac{\ln 2}{2}} \frac{2^b + 1}{2^b - 1} \quad (4)$$

The angle parameter  $\Theta$  ( $\Theta \in [0, \pi]$ ) specifies the orientation of the normal to the parallel positive and negative lobes of the Gabor filters (this normal is the axis  $x'$  in eq. 2). Since a filter based on the function  $g$  will respond most strongly to a bar, edge or grating, the normal to which coincides with  $\Theta$ , the orientation specified by  $\Theta$  is referred to in the following as the preferred orientation.

Finally the parameter  $\varphi$ , which is a phase offset in the argument of the harmonic factor  $\cos(2\pi \frac{x'}{\lambda} + \varphi)$ , determines the symmetry of the function  $g_{\lambda, \Theta, \varphi}(x, y)$ : for  $\varphi=0$  and  $\varphi=\pi$  it is symmetric, or even, with respect to the centre point  $(0,0)$ ; for  $\varphi=-1/2\pi$  and  $\varphi=1/2\pi$ ,  $g_{\lambda, \Theta, \varphi}(x, y)$  is antisymmetric or odd [8].

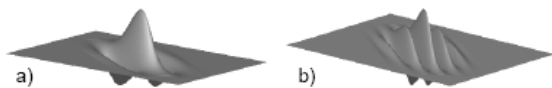


Fig. 5 Two dimensional Gabor functions with the same standard deviation  $\sigma$  but with different values of the ratio  $\sigma/\lambda$  and consequently different preferred spatial frequencies and spatial frequency bandwidths

In our project we developed the above filters to specify different fluorescence intensities into the BL bronchoscopy images.

After series of experiments we decided to use constant values for standard deviation  $\sigma$  and the parameter  $\varphi$  ( $\sigma=3$  and  $\varphi=0$ ). By choosing six different spatial frequencies (0, 2, 4, 8, 16, 32) and five different orientations (0,  $\pi/3$ ,  $\pi/6$ ,  $\pi/2$ ,  $3\pi/4$ ) we created a bank of 30 Gabor filters. We filtered the BL bronchoscopy images using the 30 Gabor filters to distinguish the regions that autofluoresce relatively different from the healthy tissue. These regions can be classified as suspicious

regions. Many of the Gabor filters worked well but the best results were produced using spatial frequency  $1/\lambda=\pi/3$  and orientation  $\Theta=16$ . Using the specific Gabor filter and certain threshold values we developed a tool that produces the filtered BL image and the original BL image marked with the regions that have different autofluorescence emission relatively with the autofluorescence emission of healthy tissue. Table III is the Gabor filter that has been used for texture analysis.

TABLE III  
GABOR FILTER

-0.3336	-0.1124	0.3557	0.6065	0.3557	-0.1124	-0.3336
-0.4405	-0.1485	0.4695	0.8007	0.4695	-0.1485	-0.4405
-0.5203	-0.1754	0.5547	0.9460	0.5547	-0.1754	-0.5203
-0.5501	-0.1854	0.5864	1.0000	0.5864	-0.1854	-0.5501
-0.5203	-0.1754	0.5547	0.9460	0.5547	-0.1754	-0.5203
-0.4405	-0.1485	0.4695	0.8007	0.4695	-0.1485	-0.4405
-0.3336	-0.1124	0.3557	0.6065	0.3557	-0.1124	-0.3336

### III. RESULTS

We tried to develop certain Matlab<sup>®</sup> tools so that the pneumonologists can easily analyze the bronchoscopy images in real time. We mainly focused on images with the blue light (BL). As for these images we used texture characteristics as smoothness, entropy and uniformity and we additionally analyzed them with the Gabor filters in order to reveal the pathological regions. The results were quite satisfactory revealing the suspicious regions clearly. The problem is to totally confirm our results with the biopsies from these regions.

#### A. White Light Image Processing Results

##### 1) Texture Analysis by using First Order Statistics

Fig. 6 depicts the final image filtered by the second tool of texture analysis. The texture filter overshadows the regions that their average gray level is similar to the average gray level of the selected region in Fig. 3. The overshadowed regions can be classified as suspicious regions.



Fig. 6 Final WL filtered image

The detection filter that uses the average grey level measure

performed effectively in the detection of suspicious regions whereas the constructed filters using the rest texture characteristics did not produce obvious results. This fact can be confirmed studying Table II, as suspicious tissue regions have quite lower values of the average gray level compared to the values of healthy tissue regions. On the other hand the values of the rest texture characteristics do not offer the ability to distinguish suspicious from healthy tissue regions.

## 2) Color Space Analysis

Converting the original WL RGB image (Fig. 1) to the HSV system, we worked on the S component. By properly thresholding the histogram of the S component (Fig. 8) we managed to detect the suspicious regions of the image. Then we produced the final image where clearly all the suspicious regions are depicted with red color (Fig. 9).

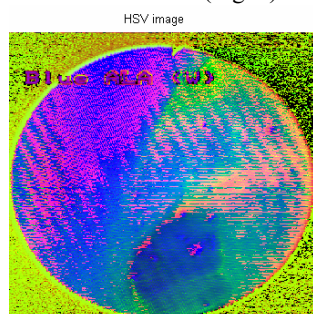


Fig. 7 The HSV color space image

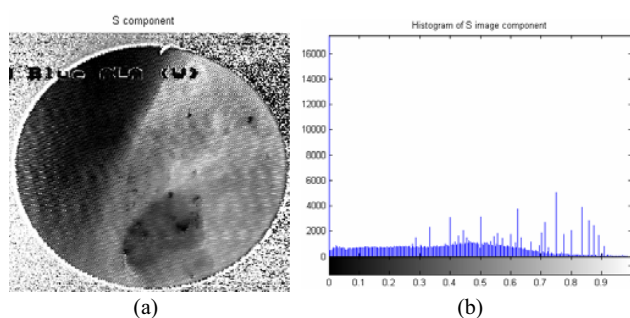


Fig. 8 The S component of the HSV image (a) and its histogram (b)

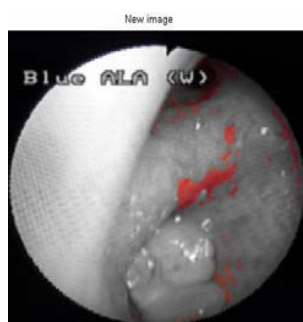


Fig. 9 The final image depicting the detected suspicious regions

## B. Blue Light Image Processing Results

### 1) Texture Analysis by using First Order Statistics

Fig. 10 depicts the original BL bronchoscopy image. Fig. 11 depicts the original image marked with the regions which the filter of smoothness displayed as regions with different autofluorescence emission relatively to the autofluorescence emission of healthy tissue. Similarly to the results of the filter of smoothness, Fig. 12 depicts the results we produced using entropy and Fig. 13 depicts the results we produced using uniformity. Observing the results of the three filtered images we conclude that the filters effectively detect common suspicious regions. However, the physicians must take seriously into consideration the uncommon detected regions.

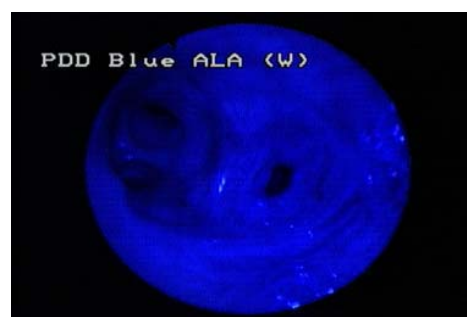


Fig. 10 Original BL bronchoscopy image

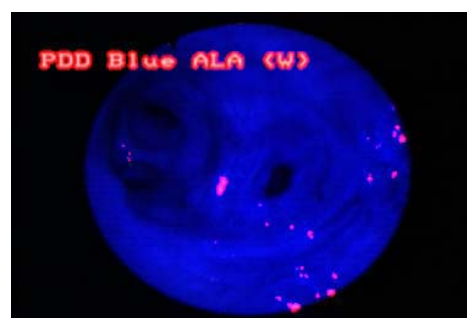


Fig. 11 Filtered image by the filter of smoothness

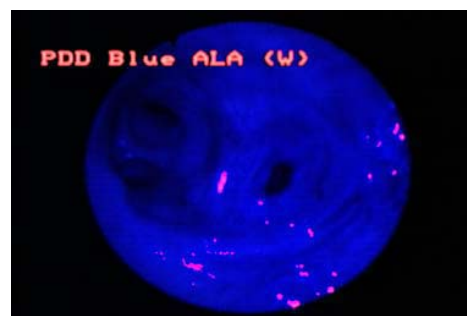


Fig. 12 Filtered image by the filter of entropy



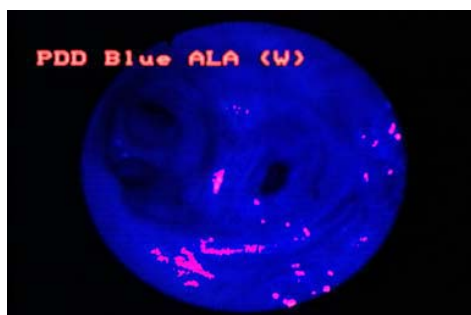


Fig. 13 Filtered image by the filter of uniformity

## 2) Gabor Filtering

Figures 14 and 15 depict the results we produced using the Gabor filter to the original BL image (Fig. 10). Fig. 14 depicts the Gabor filtered image and Fig. 15 the original image marked with the regions that have different autofluorescence emission relatively to the healthy tissue. We observe that in the specific case, Gabor filtering is more effective than texture analysis by using first order statistics.

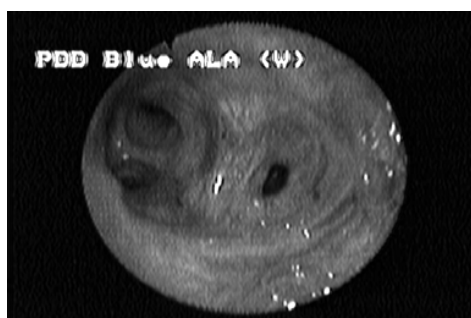


Fig. 14 Gabor filtered image

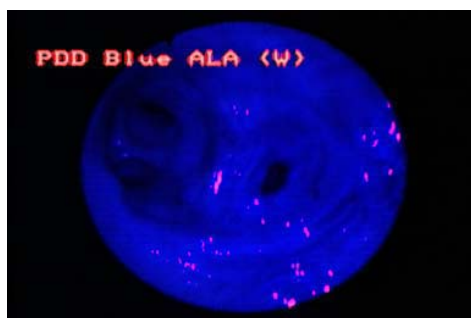


Fig. 15 Final Gabor filtered image

## IV. CONCLUSIONS AND DISCUSSION

Based on texture and color analysis techniques we managed to clearly show the regions that hide pathology.

According to our results, texture analysis techniques such as first order statistics analysis additionally to color image analysis techniques, performed effectively on WL

bronchoscopy images. Particularly best results were achieved working on average gray level texture measure and the S component of the HSV color space.

As far as BL images are concerned, best results were achieved when we used smoothness, entropy and uniformity as well as the Gabor filter we developed.

The techniques we developed and the tools we constructed are under further development at this time. We try to check the results we produced with a statistically reliable number of biopsies from the suspicious regions and from both physiological and pathological areas. According to physicians estimations the results of our tools are considerably satisfying, thus we are encouraged to continue our efforts on improving the present tools and creating new ones for even better recognition of suspicious regions.

Our efforts are now addressed to: 1) exploit the first order statistics that were useless in our experiments on WL image processing; 2) combine texture and color space analysis; 3) optimize the Gabor filter we developed; 4) research the effectiveness of other texture analysis methods on BL images such as co-occurrence matrices; 5) expand the capabilities of our tools by designing a neural network for classification and pattern recognition.

We hope that the error percentage made under the present circumstances at the hospital by faulty or misleading diagnosis will fall half of it. The PC is always connected with the Karl-Storz bronchoscope and the physicians can analyze in real time the images grabbed.

We believe that these tools can help effectively improve the quality of patients' life. We hope that future bronchoscopes will be designed to include image analysis modules in order to help the physicians achieve better results in cancer detection.

## REFERENCES

- [1] H. van den Bergh, "Early Detection of Lung Cancer and the Role of Endoscopic Fluorescence Imaging", *Med. Laser Appl.* 18: 20-26, pp 20-26, 2003.
- [2] E. Passalidou, "Early Detection of the Lung Cancer", *Pneumon* vol. 3, issue 15, Sept-Dec 2002.
- [3] N. Apostolou, M. Haritou, N. Lolis, D. Beldekis, A. Rasidakis, D. Koutsouris, "Advanced Platform for Lung Cancer Detection in Autofluorescence Bronchoscopy Images. Clinical Application at the "Sotiria" Hospital, Hellas", *J. Qual. Life Res.*, pg. 154-160, vol. 3, issue 2, 2005.
- [4] R. C. Gonzalez, R. E. Woods, S. L. Eddins, *Digital Image Processing Using Matlab*. New Jersey: Ed. Pearson Prentice Hall, 2004.
- [5] R. C. Gonzalez, R. E. Woods, *Digital Image Processing*, Addison-Wesley Publ. Co., 1993.
- [6] M. Tuceryan, A. K. Jain, *The Handbook of Pattern Recognition and Computer Vision*, World Scientific Publishing Co., 1998, ch.2.1
- [7] A. Zizzari, U. Seiffert, B. Michaelis, G. Gademann, S. Swiderski, "Detection of Tumor in Digital Images of the Brain" in *Proc. IASTEC International Conference Signal Processing Pattern Recognition & Applications*, Rhodes, Greece, 2001, pp. 132-137.
- [8] P. Kruizinga, N. Petkov, S. E. Grigorescu "Comparison of Texture Features Based on Gabor Filters," in *Proc. 10th International Conference on Image Analysis and Processing*, Venice, Italy, 1999, pp. 142-147.