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Early detection of melanoma using multispectral imaging and artificial intelligence techniques

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Abstract: Biomedical spectral imaging is a non-invasive, non-destructive method, and has an important role in melanoma detection and all skin lesions monitoring during their various stages. In addition to spatial information, it contains spectral information that describes structure such as melanin content, and melanoma thickness, which, very well improve the sensitivity and specificity of melanoma detection. This article aims to describe the design of a multispectral imaging system that utilizes Artificial Neural Networks and Genetic Algorithm (Artificial Intelligence) for spectral images classification, in order to reduce the processing time of spectral images, memory and cost of the system. All system (Hardware and Software) works as an automatic detection system for malignant melanoma, which identifies malignant melanoma and common (benign) nevi by using wavelength scanning method with; CCD camera, filters wheel, and only eight optical filters range from 430nm to 620nm. 47 study cases were imaged. Good results were obtained: the sensitivity 91.67% and the specificity 91.43%.

Keywords: Melanoma Detection, Spectral Imaging, Artificial Intelligence, Artificial Neural Networks, Genetic Algorithm, Images Classification

1. Introduction

Melanoma is a malignant disease of the skin, and called Coetaneous Melanoma (CM) or Malignant Melanoma (MM), according to definition of the American Cancer Society (ACS) and the National Cancer Institute NCI).

The early detection of melanoma aids to increase survival rates; in first stage 97% survival rate and reduce treatment cost which amounts about $1,800. vs. 15% survival rate and 170,000$ the treatment cost in fourth stage. Essentially there is no cure for late stage melanoma.

The malignant melanoma forms 5% from all skin cancer cases in men and 6% in women; it is more deathly than another skin cancers, it accounts for 80% of all skin cancer deaths [3].

In Europe: about 26,100 males and 33.300 females have melanoma diseases every year; of which more than 8,300 males and 7,600 females die. In the USA, approximately 6,000 people die annually of melanoma out of 60,000.

There are worldwide efforts towards prevention, diagnosis and treatment of melanoma incidence, but melanoma continues to rise at an alarming rate [2].

The correct diagnostic is the key for any successful treatment. The difficulty of clinical melanoma diagnosis by visual examination in early stage and dependence on the dermatologists' performance and experience [3,7], and the subjectivity of diagnostic judgments [5], all those reasons emerged a need to the Automated diagnostic of malignant melanoma. The Automated diagnostic of malignant melanoma increases the cost effectiveness for treatment, reduces the detection time for illness, and reduces the patient psychiatric stress caused by biopsy sampling (may be benign lesions).

2. Spectral Imaging

2.1. Historically

The first use of spectral imaging was airborne mineral mapping in the late seventies of the past century. The invention of the Charge-Coupled Device (CCD) aided in development of spectral imaging.

In 1986, the Geophysical and Environmental Research Imaging Spectrometer (GERIS) was the first commercial airborne hyperspectral imaging spectrometer.

In 1989, the NASA/JPL received Airborne Visible/IR Imaging Spectrometer (AVIRIS) that was a quality advancement in history of spectral imaging, which used 220 spectral bands between 400nm-2500nm. The AVIRIS system spurred for production of many multispectral and hyperspectral instruments [4].

2.2. Spectral Imaging Methods

The spectral imaging is divided into many types depending on the acquiring method; Whisk-broom line array band interleaved by pixel, where the image is scanned pixel by pixel, as figure 1. It has high spectral resolution, excellent spatial resolution, and very slow time (hours).

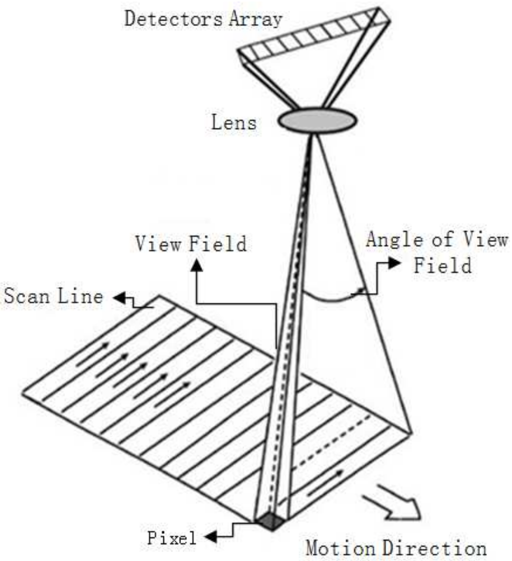

Figure 1. *Method of whisk-broom line array band interleaved by pixel.*

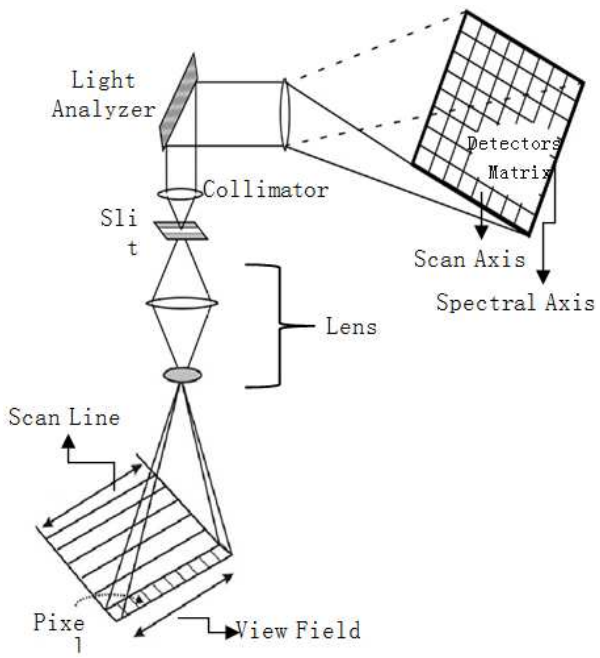

Figure 2. *Method of push-broom area array interleaved by line.*

Push-broom area array interleaved by Line (the image scanned line by line).

It has a medium-high spectral resolution, excellent spatial resolution, and is much faster (minutes), as figure 2.

The two previous types are called the spectral imaging using spatial scanning.

Framing Camera Band Sequential is another method, where the image acquired from fixed sample by capturing frames at different wavelengths which is called spectral imaging using wavelengths scanning. It has medium-low spectral resolution, medium-low spatial resolution, and very fast, (rank of seconds), as shown in figure 5. This method uses Liquid Crystal Tunable Filter (LCTF), Acousto-Optical Tunable Filter (AOTF), monochrome illumination of the sample at different wavelengths, or discrete Filters for selection of the useful wavelength [1].

2.3. Spectral Imaging Kinds

When the system uses 2–10 different spectral bands (discrete spectral bands) in spectral imaging system, it is called Multispectral Imaging (MSI), while it is called Hyperspectral Imaging (HSI) when it uses more than 10 bands [6]. Figure 3. illustrates a comparison between the multispectral imaging and the hyperspectral imaging.

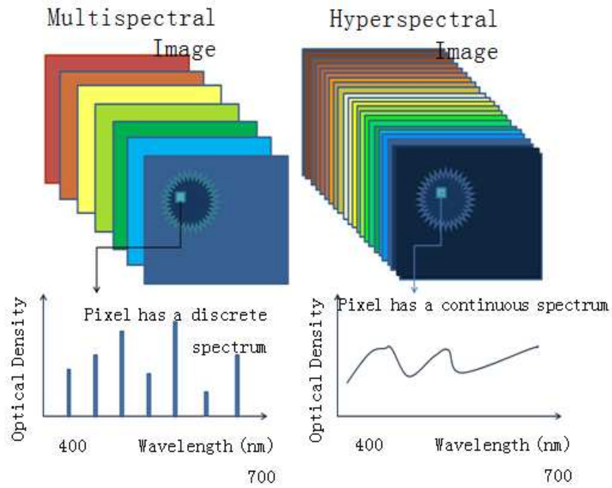

Figure 3. *Comparison between Multispectral Imaging and Hyperspectral Imaging.*

3. Material and Methods

3.1. Hardware

The wavelengths scanning method is suitable for medical applications and filters wheel is a cheaper tool in comparison with tunable filters (LCTF or AOTF), and faster.

The multispectral imaging system acquires spectral image as a Three-Dimensions data cube $I(x, y, \lambda)$, as illustrated in figure 4. The 2-dimensional image (x, y) contains the spatial information of a sample, the third dimension (λ) records spectral information, and I is Optical Density (OD). The spectral image shows the spectral information for each pixel.

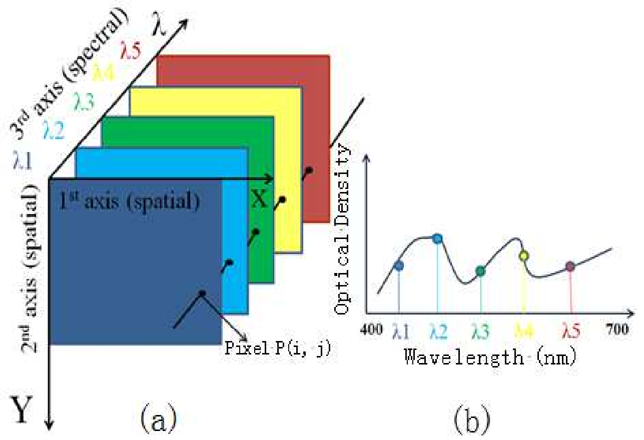

Figure 4. *(a) Data cube of multispectral image, (b) Spectrum of P(i, j).*

The multispectral imaging system is composed of: a Charge Coupled Device monochrome camera (PixeLINK, 0.8Megapixel), a filters wheel with programmable stepper motor, a one inch diameter optical filters (eight filters) ranging from 430nm to 620nm with an optical lens (objective) that has a view field equals 16º, and a Personal Computer (PC), figure 5.

The personal computer leads the filters wheel at simultaneity with camera capturing. And it stores the sequential frames (band-sequential), does the spectral images processing, and displays the result of diagnosis: benign nevi or malignant.

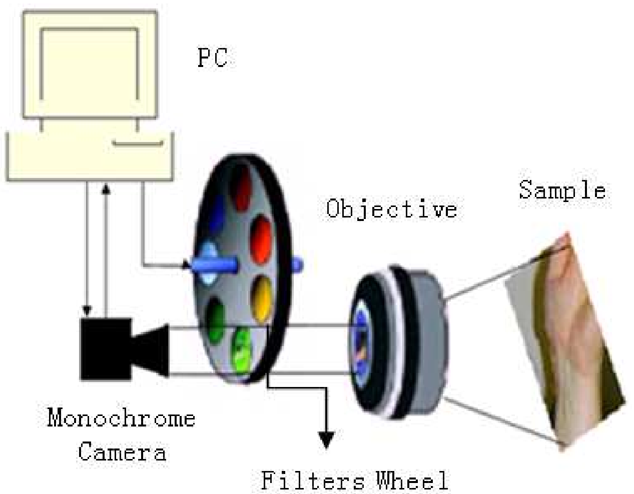

Figure 5. *Multispectral Imaging System, wavelengths scanning method.*

3.2. Software

This paper presents the Artificial Neural Networks (ANNs) as a useful technique for spectral images classification, where it works as a parallel distributed processor, and can handle the data cube of multispectral at one batch. It reputes advanced method for images classification, because it can solve problems which are nonlinear, complex and high dimensions but it is difficult to get optimal architecture.

This paper uses another artificial intelligence technique called Genetic Algorithms (GA), which has two applications for Neural Networks; optimal architecture to ANNs, and optimal training weights. Generally; Genetic Algorithm is a stochastic global search algorithm, used to solve optimization problems, and always finds a good solutions, it can handle large, complex, and multimodal search spaces.

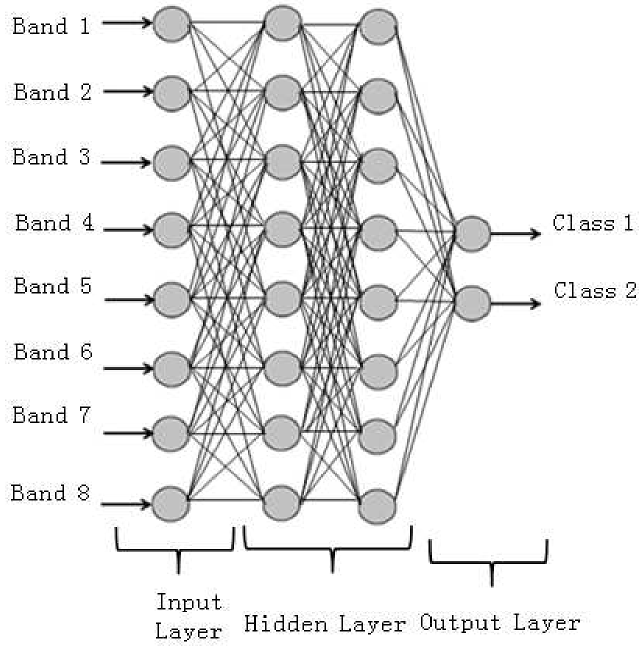

Figure 6. *Optimal ANN by GA.*

The use of GA produced a feed-forward neural network that contains two hidden layers with sixteen neurons, which is a very suitable architecture for this objective. Figure 6 displays the optimal ANNs which is obtained from applying GA to ANNs.

MATLAB language ensures a suitable environment for building the code, as High Level Language (HLL), because it includes many preconceived functions.

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4. Procedure of Imaging

The clinical study was carried out in university hospitals at Damascus University and Tishreen University, according to the following steps:

- Patient enters into special clinic and relaxes (about 3 minutes).
- Camera is focused on the region of interest (about 1-4 minutes).
- Images capturing (about 2 minutes).
- Spectral images processing and results display (about 15 second).
- The total process time is about 10 minutes, which is

considered optimal time for this process.

5. Results and its Evaluation

Forty seven study cases were imaged by multispectral imaging system; 12 cases had malignant lesion, and 35 had benign lesion. Table 1 helps us to find the Confusion Matrix (CM) for calculating sensitivity and specificity.

$$CM = \begin{pmatrix} n_{11} & n_{12} \\ n_{21} & n_{22} \end{pmatrix}$$

Table 1. *Findings of confusion matrix*

		Predicted Classification		Total True
		C_1	C_2	
Desired	C_1	$n_{11} = 11$	$n_{12} = 1$	$Row_1 = 12$
Classification	C_2	$n_{21} = 3$	$n_{22} = 32$	$Row_2 = 35$
Total Predicted		$Col_1 = 14$	$Col_2 = 33$	$N = 47$

The evaluation roles of classification are:

The sensitivity calculated from following equation:

$$\text{Sensitivity}(C_i) = \frac{n_{ii}}{\text{Row}_i} \times 100 \quad (1)$$

The specificity calculated from:

$$Specificity(C_i) = \frac{N-(Row_i+Col_i-n_{ii})}{N-Row_i} \times 100 \quad (2)$$

The classification accuracy:

$$\text{Classification\_Accuracy} = \frac{\sum n_{ii}}{N} \times 100 \quad (3)$$

The classification error:

$$\text{Classification\_Error} = \frac{N - \sum n_{ii}}{N} \times 100 \quad (4)$$

For our study:

C_1 = Malignant Lesion.

C_2 = Benign Lesion.

The sensitivity of malignant lesion can be calculated by equation (1):

$$\text{Sensitivity}(C_1) = \frac{11}{12} \times 100 = 91.67\% \quad (5)$$

The specificity of malignant lesion can be calculated by equation (2):

$$\text{Specificity}(C_1) = \frac{47-(12+14-11)}{47-12} \times 100 = 91.43\%$$

The classification accuracy can be calculated by equation (3):

$$\text{Classification\_Error} = \frac{47-43}{47} \times 100 = 8.51\%$$

The classification error can be calculated by equation (4):

$$\text{Classification\_Accuracy} = \frac{11+32}{47} \times 100 = 91.49\%$$

The result of sensitivity and specificity (for melanoma detection) is very good (>91%).

Use of GA in building and training the neural network enhances performance of ANN in comparison with previous studies in this field [7,8].

6. Conclusions

Wavelength scanning using filters wheel is good acquisition method as long as the region of interest does not move, otherwise, captured images are addles.

The use of Neural Network simplifies spectral images classification, as non-parametric method, where it can process all frames in parallel at the same time. Furthermore, application of Genetic Algorithm aids to obtaining an optimal architecture for the Neural Network.

Increasing of neurons number gives more classification accuracy, but if the total number of neurons (in hidden layers) is more than 17 neurons, neural network may saves multispectral image during training phase. Therefore, number of neurons must be more than five to achieve reasonable is up to 16 neurons. Also increasing size of study case (if it's possible) helps to increasing classification accuracy.

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