

Multispectral Image Processing Applied to Dermatology

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Abstract

Human skin is a complex surface, with fine scale geometry that makes its appearance difficult to model. Also, the conditions under which the skin surface is viewed and illuminated greatly affect its appearance. The skin can easily be examined with the eyes; however, many particular aspects of the skin are better evaluated by non-invasive imaging methods.

The goal of any imaging methodology used in dermatology is to diagnose skin disease. The diagnosis and successful treatment is often supplemented with permanent monitoring of suspicious skin lesions. Besides using computerized means, the diagnostic information can also be stored in order to use it for further investigations or creation of new methods of diagnosis. Due to the specificity of the skin, the model of light propagation inside the skin (epidermis and dermis) will have to be taken into account.

The M2D+ team has developed an imaging system called "Asclepios", a multispectral imaging system, as it allows acquiring and processing of a series of monochrome images. After acquiring a sequence of mono-channel images (this sequence is called a multispectral image), the system process a spectrum for each pixel, the set of these spectra is termed as the spectral volume (x, y for spatial, z for spectral dimension). For processing the spectral volume, in order to "eliminate" different components (e.g. the light radiance) from the images, the model of propagation of the light, termed as "Spectral Model of Acquisition" proposed by A. Mansouri and secondly on a method to reconstruct spectral volume has already been implemented for the system.

The main aim of this thesis is to write the state of the art of imaging system for the analysis of skin lesion and their comparison with our system, followed by the state of the art of the methodology already present for the analysis of the multispectral image analysis of skin lesion and at the end, implementation of the image processing technique to further process these monochrome images, in order to diagnose the presence of lesion, its internal dark island and finally contouring of these lesions.

We have tested our technique, initially on monochrome images with in the range of 400nm to 1000nm, secondly on spectral reconstruction and at the end on Luminance parameter of RGB images. The algorithm was able to successfully contour most of the data. Later we had compared the results by visually analyzing the lesions.

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Chapter 1

Introduction

There are many different types of skin cancer, and of the most dangerous among them is Melanoma, caused from unprotected high exposure to UV radiation. The dramatically increasing incidence rate of cutaneous melanoma has prompted doctors and specialists to investigate the lesion condition in its early, curable phase. Fortunately, early detection of this skin cancer can improve the cure rate. However, if the melanoma is not detected in its early stage then even some times the chances of survival are rare. Most general practitioners have less experience in the full range of melanoma forms, and because of this, many melanoma cases are not diagnosed properly. The current primary method for detecting melanoma relies on dermatologist to interpret whether a pigmented skin lesion is suspicious for melanoma based on their experience and ability to recognize patterns using clinical examination, as the skin can easily be directly examined with the eyes. The experienced dermatologist relies initially on pattern recognition, second on history, and later on laboratory parameters. Generally, Physicians follow the “ABCDE” criteria, Asymmetry, Border irregularity, Color variation, Diameter, and Evolving in ABCD, in their assessment. However, many particular aspects of the skin can not be evaluated effectively with the naked eye e.g. morphology, as skin is composed of many superimposed layers, with different characteristics, properties and functions that cannot be differentiated by the naked eye but are clearly delineated by imaging methods. Advances in digital dermoscopy, microscopy, imaging, and photography have formed an impressive arsenal with which dermatologists can better diagnose the problem and at the same time can improve their academic and research capacities.

Many attempts have been made to automate the detection and classification of melanoma from the digital color and surface reflectance images. Those attempts initially involve the segmentation of the skin lesion from the surrounding skin followed by the calculation of

classification features. Accurate description and measurement of image features cannot be achieved without accurate image segmentation. Therefore, a wide range of algorithms have been proposed in the past for color image segmentation, broadly categorized as pixel-based segmentation, region-based segmentation and edge detection with varying success. However, in the case of spectral reflectance images, the research is still limited and only few algorithms have been proposed which works on the limited range of wavelength. The present thesis deals with the implementation of a specific segmentation method. It allows the data analysis issued from the reconstruction of multispectral images for the evaluation of different skin lesion.

The current thesis is organized as follows:

In **Chapter 2**, we explain in detail about the problem in detecting skin lesion and at the same time we proposed the solution. **Chapter 3** deals with the available current techniques for skin imaging along with the system available for the diagnosis of skin lesion, Further more, in this chapter we have discussed about the comparison of different Multispectral system. **Chapter 4** describes about the hardware and the Principle of our system. In **Chapter 5** we present the state of the art of Segmentation technique for the detection of skin lesion. Methodology is explained in **Chapter 6** and we present the results in **Chapter 7** .At the end we propose the future work.

Chapter 2

Problem Definition

Skin lesion color is an important feature for diagnosing malignant melanoma. In previous research, skin lesion color was investigated for discriminating malignant melanoma lesions from benign lesions in clinical images. As, human skin is a complex surface, with fine scale geometry makes its appearance difficult to model and also, the conditions under which the skin surface is viewed and illuminated greatly affect its appearance.

The knowledge that light of different wavelengths penetrates the skin to different depths led the researchers to evaluate pigmented lesions under specific wavelengths of light from the infrared to near UV range. Multi-spectral imaging can capture light from frequencies beyond the visible light range, such as infrared. This can allow extraction of additional information that the human eye fails to capture with its receptors for red, green and blue. For the accurate reproduction of the original color through digital imaging systems, the multispectral imaging technology is promising. By using the spectral information, the reproduced color accuracy is considerably improved as compared to conventional RGB based systems. Moreover, the spectral information can be employed for the analysis or the information retrieval about consistence and concentration of absorbers and reflectors in the skin. The different pigments of skin absorb different light wave, which helps in determining the reflectance coefficient of the area of the skin.

The important aspect of surface spectral reflectance is the property that the spectral reflectance curve is based on the material composition of the object surface, which can be helpful to recognize objects and segment regions in the illumination invariant way. Sequences of images taken at different wavelengths of light are called multispectral images. Multispectral imaging technology has been applied to dermatology mainly for the diagnosis

of melanomas. Currently there are only few systems, e.g. spectrophotometric intracutaneous analysis (SIA) scope, MelaFind and SpectroShade, which use multispectral dermoscopic images as the inputs for subsequent computer analysis.

To our knowledge, the system which has already developed for the analysis of skin lesion from multispectral images, takes the images on selected wavelength and then evaluate the images on those fix wavelength. However, as different skin lesions can be investigated much better on some specific wavelength. Therefore, in order to find relative best results on some specific wavelengths, the proposed system analyzed the lesion on most of the wavelengths, as compared to the previous system, which analyzed on at most 10- 16 wavelengths. The system proposed in this thesis is based on one of the proposed approaches for the spectral volume reconstruction of skin lesion images. The system allows to process a spectral reconstruction, by obtaining a spectral volume (x, y, z) , x and y for spatial and z for spectral dimension. The two approaches has been proposed for this task, they include analysis of the skin plane by plane (one spectral plane is chosen) and analyse the skin for one pixel (one spectrum). The scope of this thesis is limited to the implementation of plane by plane technique for the evaluation of skin lesions. The implemented segmentation algorithm is based on the technique proposed by Carrara et al for the automatic segmentation of multispectral skin cancer and other pigmented lesions images. This method first reduces an image into an intensity image and approximately segments the image by intensity thresholding followed by the edges refinement. Double thresholding is used to focus on an image area where a lesion boundary potentially exists.

Chapter 3

Skin Imaging Techniques and System

Dermatology is often termed as a visual specialty wherein a majority of diagnoses can be made by visual inspection of the skin. Diagnosis of skin disease in dermatology is largely noninvasive. The physician diagnosis is based on the anatomic distribution, color, configuration, and visible surface changes of a lesion. In some cases, a skin biopsy is performed which again offers the opportunity for a microscopic visual examination of the lesion in question, but there exist limitations in the assessment of depth and size of skin lesions as well as internal features of superficial lesions. Such limitations results in need for an objective noninvasive means of assessing the skin.

Digital dermatoscopic images firstly have to be parameterized for automatic classification. The deep study of skin nature has to be done before to parameterize it.

3.1) Physical Properties of Normal Skin

3.1.1 Skin Structures

The skin consists of an epidermis, dermis and subcutaneous fat. Many skin diseases characteristically affect a particular layer of the skin. For extraction skin or lesion optical features

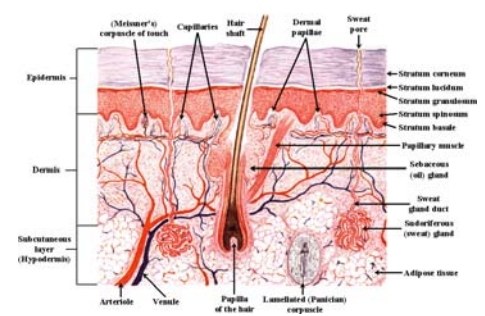


Figure 1: Internal Layers of Skin

it is very useful to use multi layer skin model. The most common is four-layer skin model: Stratum Corneum, Epidermis, Papillary dermis and Reticular dermis. Stratum Corneum is top thin layer, which is a protective layer consisting of keratin-impregnated cells and it varies considerably in thickness. Apart from scattering the light, it is optically neutral.

3.1.1.1) Epidermis

The epidermis is largely composed of connective tissue. It also contains the melanin producing cells, the melanocytes, and their product, melanin. In this layer there is strong absorption of blue and ultraviolet light. Melanocytes absorb most of this light. It behaves like blue and ultraviolet filter, which characteristics depend on concentration of melanocytes. Within the epidermal layer there is very little scattering, with the small amount that occurs being forward directed. The result is that all light not absorbed by melanin can be considered to pass into the dermis [1].

3.1.1.2) Dermis

Dermis consists of two sub layers: papillary dermis and reticular dermis. Dermis itself consists of collagen fibers and, in contrast to the epidermis; it contains sensors, receptors, blood vessels and nerve ends. In papillary dermis the collagen fibers are thinner and they behave as highly backscattering layer. Any incident light is backscattered towards surface. Scattering is greater in red spectrum and going greater to infrared. Because infrared is not absorbed by melanin and blood, this part of spectrum is best for assessing thickness of papillary dermis [1].

3.1.1.3) Subcutaneous fat

The subcutaneous fat is composed of adipose tissue separated by connective tissue trabeculae containing blood vessels, nerves and lymphatics. It serves both as insulation and a caloric reservoir. Its thickness also varies depending upon anatomic location, sex and body habits [1].

3.2) Skin Imaging

Imaging modalities with major relevance to skin imaging include various modification of electromagnetic wave imaging (Optical, Infrared, Terra Hertz, Nuclear Magnetic Resonance), acoustical wave imaging, mechanical wave imaging . Usually tomographic images i.e. 2D cross sectional images are acquired with medical imaging system. Depending on the spatial orientation of the cross section, these images depict information about the tissue over depth or any other direction. Three dimensional tissue volumes are usually imaged by acquiring a stack of consecutive 2D images [25].

The different illumination method called epiluminescence can be used in order to get the image from deeper skin layers. The light is directed straight in to these layers and reflected goes back through lesion giving more information about consistence of light absorbers in these layers. This method of illumination improves diagnosis accuracy up to 10 percents. Another interesting solution of getting more information from skin is using multi spectral photography, which uses narrow frequency bands of light illumination. Those images give information about consistence and concentration of absorbers and reflectors in the skin. The idea is that different pigments of skin absorb different light waves, determining the color of our skin. When those photos are made with range of light waves, we can calculate the reflectance frequency characteristics of skin. And comparing to normal skin characteristic there can be made diagnostic decisions about skin pigment consistency. Some of the methods based upon the above classification of skin imaging are described in next coming sections [2].

3.2.1) Dermoscopy

Dermoscopy, also called Dermatoscopy, is a diagnostic technique that is used worldwide in the identification and diagnosis of numerous skin lesions. Accuracy in diagnosing melanoma has been shown to be increased following training in Dermoscopy [3].

- Used for a more accurate diagnosis of early skin cancers.

- Also known as Skin Surfacing Microscopy, a non invasive diagnostic technique for the observation of pigmented skin lesions, allowing a better visualization of surface and subsurface structures. This diagnostic tool permits the recognition of structures not visible by the naked eye.

There are some signs to look for when diagnosing whether a lesion is a melanoma or not [3]. A common Dermoscopy rule is the ABCD rule which considers these 4 main factors:

Dermoscope is a non-invasive, diagnostic tool which visualizes subtle clinical patterns of skin lesions and subsurface skin structures not normally visible to the unaided eye. It has also been called a skin surface microscope, epiluminescence microscope or episcope. Basically, a dermoscope is functionally similar to a magnifying lens but with the added features of an inbuilt illuminating system, a higher magnification which can be adjusted, the ability to assess structures as deep as in the reticular dermis, and the ability to record images[4].



Figure 2: Representation of ABCD rule (Images have been taken using a Dermoscope)

3.2.1.1) Principle

The basic principle of dermoscopy is trans-illumination of a lesion and studying it with a high magnification to visualize subtle features. Light incident on skin undergoes reflection, refraction, diffraction and absorption. These phenomena are influenced by physical properties of the skin (Figure 3). Most of the light incident on dry, scaly skin is reflected, but smooth, oily skin allows most of the light to pass through it, reaching the deeper dermis.

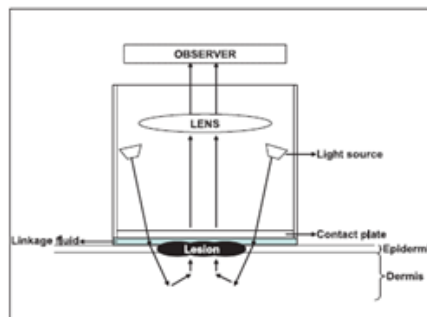


Figure 3: Optics of Dermoscope. The refracted light tranilluminates the lesion while passing through it and is perceived as a distinct pattern.

Dermoscope can mainly be classified as:

- a) Dermoscope without image capturing facility
- b) Dermoscope with image capturing facility
- c) Dermoscope with image capture facility and analytical capability.

3.2.1.2) Technique

Dermoscopy can be done by either the non-contact or the contact technique. In the contact technique, the glass plate of the instrument comes in contact with the surface of the linkage fluid applied lesion. In contrast, in the non-contact technique, there is no contact of the lens with the skin; the cross-polarized lens absorbs all the scattered light and hence allows only light in a single plane to pass through it (Figure 1). While the non-contact technique ensures that there are no nosocomial infections, this advantage is overshadowed by the disadvantages of decreased illumination and poor resolution. Table 3 shows some of the available dermoscopic devices [4].

Dermoscopic Devices

S/No	Device Name	Function	Manufacturing Company
1	DermoGenius Ultra	ABCD score & comparison with reference bank	LINOS Photonics Inc
2	Fotofinder Dermoscope	comparison with a reference bank	Edge Systems Corp and Teachscreen GmbH
3	Molemax II	ABCD score & comparison with reference bank	Derma Instruments LP (Austria)
4	MicroDerm	DANAOS 8 ANN classifier	VisoMed (Germany)
5	DB_Mips	ANN & similarity classifier	Scientific Informations (italy)

Table 1: Dermoscopic Devices

3.2.2) Image Analysis and Computer Assisted Diagnosis

Advances made in computer technology, digital imaging, and computer programming have been applied by researchers to explore their potential uses in the evaluation of pigmented cutaneous lesions. Numerous computer programs have been created to objectively document the clinical features of digitized pigmented lesion images. Most of these systems rely on sophisticated programs for lesion segmentation, which determines the boundary separating the lesion from the surrounding normal skin.

Once the computer has identified the lesion, the program attempts to extract features that the programmer determined to be important such as number of colors, hue, texture, degree of asymmetry, degree of border irregularity, diameter, linear dimensions, perimeter, length, and area. Attempts have been made to create automated programs designed to extract relevant information from digitized clinical images and automatically assess the degree of change compared with previously taken images of the same lesion, and provide a provisional diagnosis [5].



Figure 4: Computer programme have the capability of performing lesion segmentation

The knowledge that dermoscopy adds complementary information to the clinical examination led to the development of specialized digital cameras that can capture both clinical and dermoscopic images. These digital images can be used to document pigmented lesions and allow comparisons of changes over time [5].

3.2.3) Multispectral imaging

Surface-spectral reflectance of an object is an inherent physical property of its surface. One important role that the surface-spectral reflectance plays is to supply the physical basis for the perception of an object's color.

Another important aspect of surface-spectral reflectance is the property that the spectral reflectance curve is based on the material composition of the object surface. These can be helpful to recognize objects and segment regions in the illumination invariant way. The usual camera system with three channels of RGB has difficulty in estimating surface-spectral reflectances of objects because surface reflectances in natural scenes are spectrally high dimensional. The knowledge that light of different wavelengths penetrates the skin to

different depths led investigators to evaluate pigmented lesions under specific wavelengths of light from the infrared to near UV range (Table VII). Sequences of images taken at different wavelengths of light are called multispectral images. Currently there are only few systems, spectrophotometric intracutaneous analysis scope (SIAscope) and MelaFind, which use multispectral dermoscopic images as the inputs for subsequent computer analysis [5].

S/No	Device Name	Function	Manufacturing Company
1	MelaFind	Contact Spectral Imaging with automated Diagnosis	Electro Optical Sciences, Inc (USA)
2	SIAscope	spectral Imaging	Astron Clinica (UK)

Table 2: Devices based on the Multispectral Imaging Approach

3.2.4) Ultrasound

In recent years, ultrasound scanning has become an important diagnostic tool in dermatology. There are 2 basic types of ultrasonography with dermatologic applications. The best established is 20-MHz scanning, which can be used to measure tumor thickness and/or skin thickness when treating inflammatory diseases such as scleroderma or psoriasis. Real-time sonography with 7.5- to 10-MHz probes has assumed an increasingly important role, since it is used to search for subcutaneous tumors in a variety of clinical settings, including preoperative staging and follow-up of melanoma [6].

3.2.4.1) Principle:

The ultrasound images are created due to the different acoustic properties of tissues. High-frequency sound impulses are transmitted into the skin and then reflected, refracted, or inflected when a tissue interface with different acoustic impedance is encountered. The amplitude of the intensity of the reflections at different depths in the skin is then plotted onto a display screen to give a one-dimensional graph, known as A-mode (amplitude display). The vertical cross-sectional image, which is the more familiar display of ultrasound data, is called B-mode scanning (brightness display). B-mode scanning uses the brightness level of multiple A-scans to build a 2-dimensional image. The current technology available also allows 3-dimensional C-mode (computed) scanning of structures in skin in vivo. The C-mode scans may provide a superior image compared with B-scans, however, C-scanning

remains experimental. Dermatologic ultrasonography of the skin layers is carried out with high-frequency scanners of 20 to 50 MHz, which are designed for sharp focusing at superficial focal regions, such as the skin. In contrast, the lower frequency 3- to 10-MHz scanners are used for subcutaneous or lymph node examination. The 20-MHz ultrasound and, more recently, experimental higher frequency (50-100 MHz) transducers [120-122] have been used to examine melanocytic lesions. The frequency of the ultrasound transducer determines the penetration and resolution of the imaging system [7].

3.2.4.2) Advantages and Disadvantages

The advantages of ultrasound over other imaging techniques relate to its capability, versatility, portability, safety, and economic feasibility. Commercially available ultrasound imaging systems are capable of spatial resolution approaching that of magnetic resonance microscopy as a result of advances in transducer and computing technology. Ultrasound visualization is usually used to measure depth of melanoma. The other uses of ultrasound are limited by very little tissue differences between normal skin and lesion. If there is no melanoma practically there is no any differences. When doctor diagnoses melanoma, then he uses high frequency ultrasound (over 30 MHz) to measure penetration depth in order to make correct cut during surgery. Ultrasound imaging also has limitations and disadvantages as a research tool. One particular limitation is that it requires the knowledge and expertise of a well-trained and skilled operator/sonographer to obtain accurate, repeatable, high-quality images [8].

3.2.5) Optical Coherence Tomography

OCT is a new non-invasive approach for real-time in vivo tissue characterization. OCT derives from low-coherence interferometry, able to obtain two- and three-dimensional (2D and 3D) cross-sectional imaging of the skin within a few seconds. The method uses light radiation delivered from a low coherence source (superluminescent diode) operating at a wavelength of about 1300nm (near infrared).

3.2.5.1) Principle

Optical coherence tomography (OCT) is analogous to ultrasound B imaging, except that it uses light rather than sound waves. It is described as an intermediate imaging device between ultrasound and Confocal Scanning Laser Microscopy (CSLM) [5]. The OCT technique is based on the principle of Michelson interferometry. A pulse of near infrared, low-coherence light is split such that half of the beam is sent to the specimen and half to a scanning reference mirror. The light to the specimen is focused on the papillary skin layers, backscattered, and recombines with the other reference beam of light that has reflected from the mirror system. An interference signal is only detectable when the optical paths of both arms match within the coherence length of the light source (Figure 5).

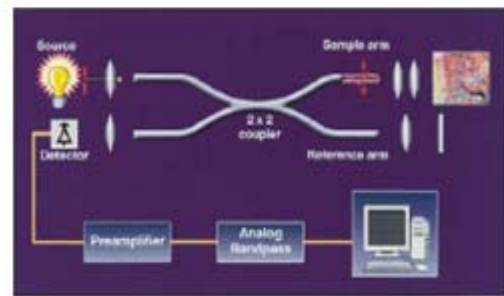


Figure 5: Principle of Optical Coherence Tomography

Measurement of the interference pattern allows determination of the position within the tissue where the light was reflected. It is the reflectiveness of different components of tissues, such as cell membranes and melanin that provides contrast in the images. A 2-dimensional cross-sectional image is built up by lateral scanning across the tissue [5]. However, acquiring two-dimensional OCT images is not sufficient to fully describe the three dimensional morphology of biological samples under study. A few research groups reported the reconstruction of three dimensional maps of reflectivity obtained by acquiring two-dimensional arrays of adjacent OCT scans, but such a procedure can be time consuming.

3.2.5.3) Advantage and Disadvantages

To image the deeper layers of the skin with a better resolution than ultrasound, a technique is needed that more effectively reduces the effects of multiple scattering. Optical coherence tomography (OCT) or low coherence tomography improves multiple scattering rejection compared to that of achieved by conventional confocal microscopy, while maintaining adequate signal strength at low light levels.

The OCT pictures are represented as two-dimensional cross-sectional images, which can be compared with B-mode high frequency ultrasound scans, but represent optical and not acoustic inhomogeneities of the tissue [10].

3.2.6) Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) has also been used experimentally in the examination of pigmented skin lesions (Figure 6). The application of MRI to dermatology has become practical with the use of specialized surface coils that allow higher resolution imaging than standard MRI coils. At this point in time, however, the technology remains experimental with no specific dermatologic applications established [11].

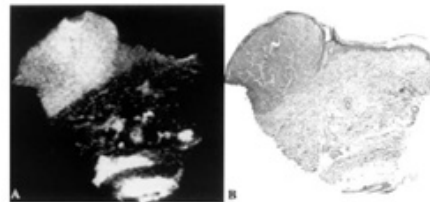


Figure 6: Magnetic resonance Microscopy of malignant melanoma(A) and corresponding histology(B)

However, recently MRI is finding an interesting clinical application in evaluating skin tumors (Maurer et al, 1995). Because the thickness of the skin is small, MRI of the skin demands high resolution and high sensitivity. Recent developments in surface coil technology and high field scanners have made MRI useful to study superficial skin structures at high resolution (Idy-Peretti et al, 1998; Richard et al, 1991).

The application of MRI in dermatology can give a detailed picture of a tumor and its depth of invasion in relation to adjacent anatomic structures as well as delineate pathways of tumor invasion. The in vivo MRI in medical diagnosis has been reported to differentially evaluate malignant melanoma tumors (Maurer et al, 2000) and subcutaneous and pigmented skin of nodular and superficial spreading melanoma [11].

3.2.6.1) Principle

Magnetic resonance imaging (MRI) is a highly flexible technique for making images of the human body. Hydrogen nuclei (protons) behave like small magnets, so that when a subject

lies in a magnet the protons tend to align with the magnetic field. When properly excited the protons precess (rotate), producing a measurable signal in a nearby detector coil. The frequency of precession is proportional to the local magnetic field, so by making the field vary across the body the signals arising from different locations can be distinguished based on their frequency. There are three basic components to an MRI system: 1) a large, static magnetic field (e.g., 3 Tesla for the human imagers at the Center); 2) radio frequency (RF) coils that are used as a transmitter to excite the MR signal, and as a receiver to detect the MR signal; and 3) gradient coils that are pulsed on and off to produce linear gradients of the magnetic field for imaging. MRI techniques involve pulsing currents through the RF and gradient coils, so a particular technique is often referred to as a pulse sequence. By varying the pulse sequence, one can produce an enormous range of images with different spatial and temporal resolutions, and with substantially different contrast between tissues in the image [12].

3.2.6.3) Advantages and Disadvantages

MRI is more advantageous over other radiological techniques in analyzing some tissues. One of the most important advantages of MRI is its capacity for displaying soft tissue contrast. Image contrast can be tailored to the specific clinical application so that specific types of pathology are emphasized[13]. The cellular distribution of water with or without increase in global tissue water is different in cancerous tissue than that of normal skin. The increase in total proton density associated with changes in water structure alters free mobile protons in epidermis, dermis, and subcutaneous tissue. These changes reflect as contrast and brightness in MRIs [11].

The potential benefits of MRI are numerous; however, there are hazards intrinsic to the MR environment. These hazards may be attributed to one or to a combination of the three main components that make up the MR environment. For a properly operating system, the hazards associated with direct interactions of these fields and the bodies are negligible [13].

3.2.7) Confocal Laser Microscope

In vivo imaging of human epidermis and superficial dermis is a matter of interest for the dermatologist. The pursuit started with a magnifying glass, continues with a dermoscope and aims towards reaching new heights with the confocal laser microscope. The confocal laser microscope is a novel and interesting noninvasive tool for imaging skin lesions and subsurface skin lesions that are not visible to the naked eye or even by dermoscopy [14].

3.3.7.1) Principle

It is based on the principle that when a diode laser beam is passed through the skin, reflected light is used to construct detailed images of optical sections through the tissue (Figure 7).

A laser provides excitation light of high intensity. The laser light is reflected from a dichroic mirror. From there, it hits two mirrors which scan the laser across the sample. Emitted light from the sample gets descanned by the dichroic mirror and is focused onto the pinhole after which it gets measured by a detector, i.e., a photomultiplier tube. At any moment, only one point of the sample is observed, a complete image of the sample is never formed. The detector attached to a computer helps in building up the image, one pixel at a time. The detection of backscattered light along with differences in tissue refractive index help in high resolution of cellular detail and contrast when examining thin sections thus making staining unnecessary [14].

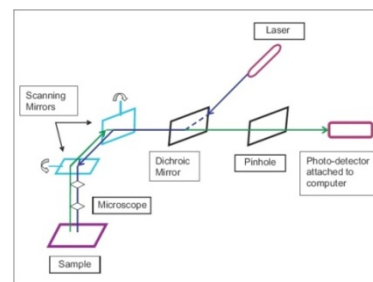


Figure 7: Principle of Confocal Laser Microscopy

3.2.7.3) Advantages and Disadvantages

The principal advantage of CSLM (Confocal Scanning Laser Microscope) is the ability to noninvasively assess the cellular components of intact skin lesions with detail approaching that of histology. Consequently, a lesion can be examined at any moment in time to determine whether it has features of melanoma and biopsy specimen– proven melanomas can be examined to determine the extent of their lateral margins [15]. Confocal microscopes

also have a higher level of sensitivity compared to conventional microscopes, due to highly sensitive light detectors and the ability to accumulate images captured over time. Disadvantages of confocal microscopy include its high cost and relatively smaller field of vision [14].

Confocal microscopy is currently in a stage of development. Newer modifications in the technique are taking place by leaps and bounds. At present, though its use is limited for the purpose of research, the confocal laser microscope may have enormous clinical implications for dermatology in future [14]. Currently available systems used in clinical conditions include VivaScope and Optiscan. The VivaScope, introduced in 1997, have been historically the workhorse confocal imagers for clinical dermatology research. VivaScope confocal imagers provide dermatologists the highest resolution noninvasive means available today to display cellular resolution images of the skin. Using advanced laser technology, VivaScope imagers can produce optical images of skin lesions with incredible cellular resolution, enabling medical professionals to see cellular morphology — in real time, in living tissue [24].

3.2.8) Comparison of All Techniques

In the previous sections, different methods were described that can be used to image the skin. In this section the performances of the various systems are discussed on the basis of one specific application of measuring skin depth.

MRI is not suited only for the specific application, due to high costs of the equipment, the extra needed environmental measures and the lack of surface coils. 20 MHz ultrasound is especially suitable to visualize the dermis and the subcutaneous fat layer. It is not suitable to distinguish the epidermis from the dermis due to the very high entrance echo reflecting the water skin surface interface. 100 MHz ultrasound can be used to visualize the epidermis and the dermis. However, due to the decreased penetration depth, the epidermal-dermal junction can only be seen at anatomic sites where the skin is thin. A large drawback of ultrasound is that it needs water as a coupling liquid, since hydration influences the mechanical properties of the layers e.g. stratum corneum[10].

OCT is comparable to 100 MHz ultrasound with respect to the visualized skin layers. Ultrasound is based on acoustic properties of the skin, whereas OCT shows the various optical properties of the skin structure. A large advantage of OCT is that it can be used with and without water. Addition of water leads to a slightly larger penetration depth. Thus OCT may be used to compare mechanical properties in case of dry and fully hydrated skin [10].

Confocal microscopy is a very promising technique which is able to visualize single cells in the superficial skin layers. Also collagen fibres can be observed in the upper part of the dermis. The different layers of the living epidermis, the stratum corneum and the papillary and reticular dermis can be clearly distinguished. Similar to ultrasound, water (or oil) is needed as coupling liquid in confocal microscopy.

The wide variety of methods shows, that there is no best universal visualization. Some of them are used for different needs, other are very expensive. Therefore, the choice of method depends on what features of skin lesions is wanted to visualize, and on availability of resources. In the next coming section few of the different devices available based on the above techniques are described.

3.3) Devices Based On Different Imaging Techniques

3.3.1) Devices based on Dermoscopy

Foto Finder

FotoFinder Dermoscope covers five dimensions of skin cancer prevention, helping you to detect both melanoma and non-melanoma skin cancer [16]:

1. Long-term observation of nevi through video documentation.
2. Time saving skin cancer screening with the digital Dermoscope.
3. Analysis of melanocytic nevi with the Mole Analyzer.



4. Detection of new and changed moles with Bodyscan pro.
5. Detection of non-melanoma skin using fluorescence diagnosis.

FotoFinder Dermoscope II offers all in one, dermoscopic skin cancer screening, total body mapping and documentation of cosmetic treatments. The modular configuration allows to add various extras for different fields of applications.

3.3.2) Devices based on Optical Coherence Tomography

SkinDex 300:

SkinDex 300 is the world's first dermatological research device based on OCT technology that has been designed specifically for series production [17].



i. **SkinDex 300 offers the following features:**

- 2- and 3-dimensional imaging with contrast enhancement.
- Skin characterisation by refractive index and scattering parameter evaluation via additional software.
- Visualisation of blood flow.
- Automatic sequential data acquisition over longer time periods.
- Simultaneous microscopic acquisition of skin surface (e.g. for positioning purposes).
- Easy access to skin regions by flexible tripod.

ii. **Advantages, Features, Specifications**

Compared to other non-destructive methods as ultrasound imaging or confocal microscopy, the optical scanner **SkinDex 300** offers significant advantages for many applications:

- Larger penetration depth as compared to confocal microscopy.
- Significantly higher spatial resolution as compared to ultrasound imaging.
- OCT and histological slides provide similar morphological information content.
- Choice of the contact medium is not critical.

3.3.3) Devices based on Ultrasound Imaging

Episcan® i-200Ddermal Ultrasound Scanner

EPISCAN-I-200 is a ultrasound based system, which has been designed to image the skin and underlying few centimetres of soft tissue with great clarity. Ultrasound of centre frequency as high as 50MHz can be utilized to provide clear images of soft tissue structure, visualise the impact of many of the diseases and injuries that inflict this region and monitor the impact of treatments[18].

The EPISCAN's software operates under Windows XP and has been designed to be user friendly as well as providing the user with a series of features and functions that allow image annotations and measurements to be performed as well as comprehensive patient record keeping. Further, digital photographs can be imported [18].



3.3.4) Device based on Multispectral Imaging

SIAcope

A new technique “Spectrophotometric Intracutaneous Analysis” (“SIA”) has been developed, commercialised and shown to have excellent sensitivity and specificity in the early identification of malignant melanoma in human skin. The technique is based upon a unique combination of dermatoscopy and contact remittance spectrophotometry. SIAscopy understands the way light interacts with skin; the manner in which it scatters or bounces, the amount absorbed by cells and other structures as well as the differences changes in wavelength or colour make. By understanding these interactions and comparing readings as light is sent into the skin and emerges back out, SIAscopy is able to determine the nature and position of many of the different cells and structures within skin [20].



In particular SIAscopy measures the amount of haemoglobin, melanin, collagen and whether melanin is in the epidermis or the dermis. The information is presented in the form of maps

called SIAscans, which show how these measurements vary over the skin. The light used by SIAscopy is completely safe and painless, which makes it a perfect technique for monitoring skin conditions.

The SIA hardware comprises a hand-held imaging probe, attached by umbilical to a laptop computer, that is placed in contact with the skin surface. High-intensity LEDs illuminate the skin surface with eight consecutive discrete wavebands between 400nm and 1000nm [19], spanning the visible spectrum and a small range of near infrared radiation. A digital image is captured for each waveband.

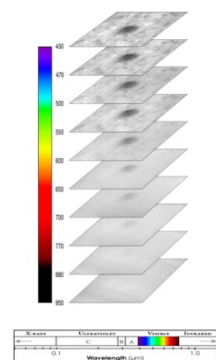
The SIA system, which is described as a skin chromophore imaging system, is one instrument currently being evaluated. The instrument performs an in vivo examination of a 12-mm diameter area of skin and captures images at different, narrow spectrum, filtered wavelengths ranging from 400 to 1000 nm peaks [19]. These wavelength-dependent images provide information on the concentration, distribution, and position of skin chromophores—collagen, melanin, and hemoglobin. Initially, the SIA algorithm determines the quantity of collagen within the papillary dermis using the infrared wave bands. Following this, it verifies the epidermal and/or dermal melanin distribution, the vessel distribution, and the topography of the dermoepidermal junction. This information is then displayed in different SIA graphs and corresponding images to assist the physician in diagnosis [20].

MelaFind

MelaFind® System, designed by **Electro-Optical Sciences, Inc.**, is thought to improve early diagnosis of melanoma.

The MelaFind® system is comprised of a point-of-care, hand-held imaging device that, in commercial use, is intended to be connected via the internet to a central server. MelaFind® employs multiple wavelengths of light to obtain data from images of suspicious pigmented skin lesions; the data are analyzed against our proprietary database of melanomas and benign lesions using our sophisticated algorithms [21].

MelaFind is another instrument using multispectral illumination of both the clinical and dermoscopic images. This instrument uses 10



different, narrow-spectrum wavelengths, from near infrared through visible light spectrum, to obtain information on the absorption and scattering properties at different depths of a lesion. This provides information about the lesion border, size, and morphology that is not available to the naked eye. A specialized imaging probe detects illumination in each spectral band, creates the digital images, and sends them to a computer for processing, all within 3 seconds. The researchers behind MelaFind aim to produce a fully automated, nonoperator-dependent, objective measurement instrument for the diagnosis of melanoma. The system uses dedicated software (algorithms) for automatic differentiation between malignant melanoma and benign pigmented lesions. It aims to differentiate in situ melanoma from invasive melanoma and may be able to reliably determine the Breslow thickness of invasive melanoma [21].

SpectroShade System

SpectroShade instruments, is an optical device based on multi-spectral image analysis of colour and shape features of pigmented skin lesion. The system utilizes the optic technology by combining dual digital cameras linked through optic fibers to a fully functioning spectrophotometer all located within a computer system. The system is mainly composed of an illumination assembly located inside a PC and an external detection device placed in a hand-held probe that has to be positioned over the skin without any interface. For each lesion, the system allows us to acquire images at 15 different spectral bands (30 nm bandwidth) between 483 nm and 950 nm. All images, acquired within a useful area of $18 \times 14 \text{ mm}^2$ are stored in the PC and then analysed by software integrated in the system, previously developed in the MATLAB programming environment. By image processing, 65 descriptors are evaluated for each lesion. In order to minimize redundant information in the data set, a factor analysis is then applied to the extracted parameters before setting up a

neural network classifier designed to perform automated diagnosis[26].

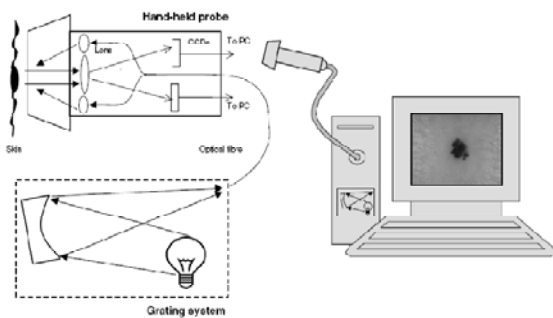


Figure 8. Schematic diagram of SpectroShade. The apparatus substantially comprises an illumination assembly, located inside the PC, a bundle of optical fibers and an illumination/detection assembly, located inside the hand-held probe. The illumination assembly comprises a halogen lamp and a diffraction grating that can be rotated by means of stepping motors. The lenses in front of the fibers contribute to a

homogeneous illumination of the skin under test. The image sensors are constituted by two CCDs, operating in RGB and B/W mode, respectively. Images from the CCDs are stored in the PC and analysed by dedicated software.

3.4) Discussion on Multispectral Imaging Devices

There are several multispectral imaging systems developed or under development to aid physicians in the diagnosis of skin diseases. These systems use illumination of the skin in different spectral bands in the visible and near infrared (IR). Spectrophotometric intracutaneous analysis (SIA) scope and MelaFind are among the available systems which use multispectral dermoscopic images as the inputs for subsequent computer analysis. Melafind uses computer analysis to provide a diagnosis in a completely automated system, where as, the Siascope uses computer analysis to generate graphs and images that require physician interpretation for diagnosis.

The SIAscope produces eight narrow-band spectrally filtered images of the skin with radiation ranging from 400 to 1000 nm [19]. Spectrophotometric analysis works on the principle that light energy is absorbed and remitted by particular target cells with colour (chromophores) in the skin. Initially the device emits visible and infrared light. Various chromophores in the layers of skin respond to the light differently and send back remitted light. Melanin absorbs ultra-violet light, Haemoglobin (red blood cells) absorb infrared light, where as, Collagen absorbs and remits light across the spectrum corresponding to the size and amount of collagen cells in the deeper layers of skin. Reflected light received by the spectrophotometer is analysed by a computer software program that calculates the quantity of light absorbed at various wavelengths. The images created from computer analysis show the presence of melanin, blood or collagen changes in the area examined [22].

MelaFind acquires images in ten different spectral bands from 430 to 950 nm [23], from near infrared through visible light spectrum, to obtain information on the absorption and scattering properties at different depths of a lesion. This provides information about the lesion border, size, and morphology that is not available to the naked eye. A specialized imaging probe detects illumination in each spectral band, creates the digital images, and sends them to a computer for processing. MelaFind is a small hand held device with a camera attached to it. The device captures images of suspected area, then compared against the existing database of images and the patient is then given feedback [21].

One such system – based on multispectral imaging - is, Asclepios, is still under the development. The system initially acquires ten images in different spectral bands from 400 to 1000 nm with hand held device. The software comprises of reconstruction process and analyzes the images either by “plane by plane” or by “in depth of pixel approach”, required result can be shown on any wavelength with in the given range. The system can also give the best result (by comparing result of all wavelengths) for specific disease. Also by applying ABCD diagnostic technique, the system can detect the presence and the state of severity for any disease with in the area. The system is different from the currently existing system, because it is a unique system which can give result on any wavelength with in the range, in contrary to the existing one, which gave results on fewer fix number of wavelength. Similarly the images were analyzed by two approaches which results in giving more reliable diagnose of diseases. In conclusion the Asclepios would be the versatile combination of clinical dermoscopic rule (ABCD) and image process techniques for multispectral images.

Chapter 4

Description of Asclepios System

Conventional color imaging defines each pixel with three variables such as red, green and blue, which are necessary and sufficient to characterize any color. In the field of colorimetric analysis of the skin, most of the current tools make use of a colour camera and only provide perceptual information about the scene. The scene acquired in one specific illuminant and it is impossible to estimate the scene color under another illuminant. Furthermore, two color samples match under one illuminant and appear completely different under another illuminant (metamerism). Multispectral imaging systems can overcome these problems to some extent by increasing the number of acquisition channels. In doing so, multispectral imaging presents the advantage of high spectral resolution over classical color imaging systems.

Similarly, the spectral analysis of the skin provides a spectrum that is specifically linked to the physical properties of the element being studied, and is independent of the light used during acquisition. It thus gives objective measurements which have high reproducibility, and makes it possible to analyse tissues using wavelengths outside the visible spectrum, in particular in UV or near-IR.

The proposed system, called Asclepios, is a multispectral imaging system, as it allows acquiring and processing multispectral images. After acquiring a sequence of mono-channel images (this sequence is called a multispectral image), processing of these spectrum for each pixel results in generating one spectral volume.

4.1) Principle of Imaging System

In the laboratory of M2D+, a system based on multispectral camera with a rotating wheel has been developed. This system is composed of a single AVT PIKE CCD based camera,

and a set of 10 interference filters. A rotating wheel, mounted in front of the camera/ lens system is equipped with 10 holes houses, akin to a rotary telephone dial, the 10 filters. It is motorized to rotate, and all are software controlled [27]. A multispectral image is acquired during each revolution and transferred to the computer (Figure 9). The system acquires the images within the range of 400nm to 1000nm, with a 50nm wide filters and the approximate duration between the consecutive filter is 60nm.



Figure 9: Hardware of Asclepios System

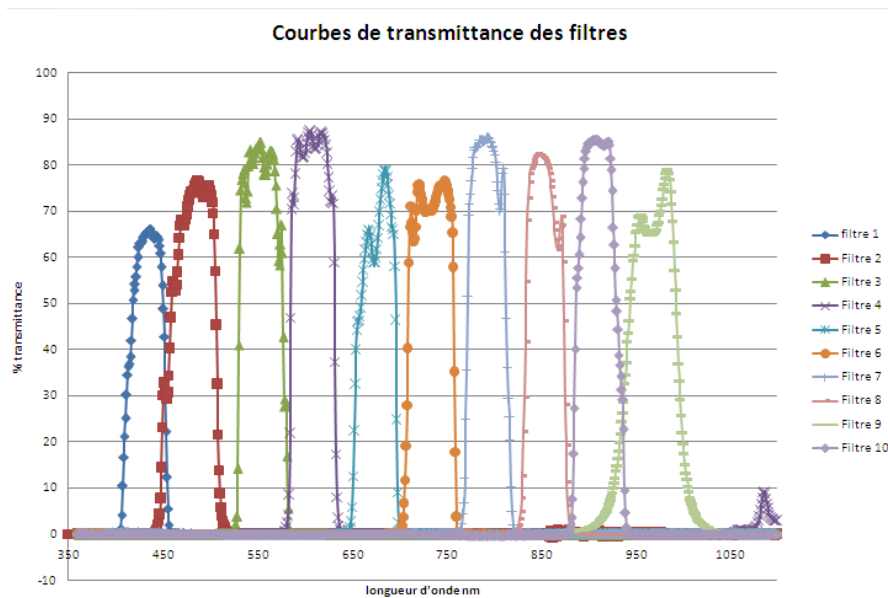


Figure 10: Wavelength range of each of the Filter

With such a system we seek to reconstruct data representing the spectral reflectance in each pixel of the imaged scene. This reconstruction is an inverse problem that means that a slight error in data completely skews the expected results. To avoid this, the system must be calibrated in order to have images of high quality. Thus, a pre-processing of the acquired channel-images is required. A channel-adapted protocol has been developed to reduce noise in such system.

4.2) Acquisition:

The system for acquisition of monochrome images is based on a prototype of one of the multispectral cameras developed by Le2i team. The current work consists in developing the algorithm for lesion detection by using this prototype that will be devoted exclusively to applications in dermatology. The tool is designed as follows:

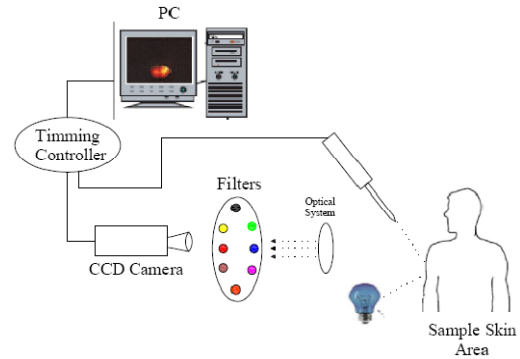


Figure 11: Schematic Diagram of Asclepios System

- The acquisition head consists of the camera, which the practitioner manipulates, is similar in size and shape to a hand-held shower.
- The head is connected to a stable QTH-type light source via a cable containing optic fibres.
- The light source is equipped with a rotating filter holder to select wavebands.
- The light is directed to the zone of skin under study and the image is captured by the camera.
- The whole apparatus is piloted by a PC to synchronise the successive exposures to the different wavebands as well as the image acquisition for each band.
- The result is a multispectral image composed of a sequence of single band images.

4.3) Processing of the Images in two steps:

4.3.1) Spectral Reconstruction

The sequence gives a series of values for every pixel. By inputting these values into an appropriately software, we obtain at the output, on a sampling basis, reflectance spectra of the corresponding zone of the skin in every pixel.

In order to process the spectral volume, some noise components (e.g. the light radiance) should initially be eliminated from the images. In the proposed system this involves two steps:

- A model of propagation of the light. This model is called "Spectral Model of Acquisition"
- A method to reconstruct spectra, for e.g. neuronal artificial network.

Spectral Model of Acquisition

The components involved in the acquisition process in a multispectral imaging system are illustrated in the “Figure 2” where $I(\lambda)$ is the spectral radiance of the illuminant, $r(\lambda)$ is the spectral reflectance of the surface, $o(\lambda)$ is the spectral transmittance of the optical system, $\phi_k(\lambda)$ is the spectral transmittance related to the k th filter and $a(\lambda)$ is the spectral sensitivity of the camera (Mansouri et al). The camera output d_k , related to the channel k for a single pixel of the image, is given by “(1)”:

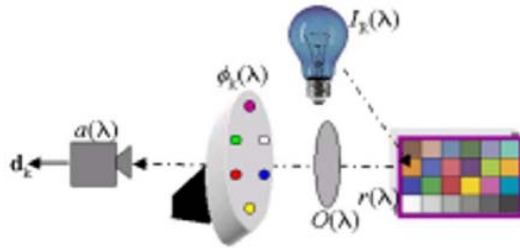


Figure12: Synopsis of the spectral Model of the acquisition process in a multispectral system

$$d_k = \int_{\lambda_{\min}}^{\lambda_{\max}} I(\lambda) r(\lambda) o(\lambda) a(\lambda) \Phi_k(\lambda) d\lambda. \quad (1)$$

By supposing a linear opto-electronic transfer function, $I(\lambda)$, $a(\lambda)$, $o(\lambda)$ and $\phi_k(\lambda)$ can be replaced by the spectral sensitivity $S_k(\lambda)$ of the k th channel. Then, the Equation (1) becomes:

$$d_k = \int_{\lambda_{\min}}^{\lambda_{\max}} r(\lambda) S_k(\lambda) d\lambda. \quad (2)$$

By sampling the spectra to N wavelengths, “(2)” can be written in matrix notations as in “(3)”

$$d_k = \mathbf{r}(\lambda)^T \mathbf{S}_k(\lambda). \quad (3)$$

$\mathbf{S}_k(\lambda)=[s_k(\lambda_1) \ s_k(\lambda_2) \dots \ s_k(\lambda_N)]^T$ is the vector containing the spectral sensitivity of the acquisition system related to the k th channel, $\mathbf{r}(\lambda)=[r(\lambda_1) \ r(\lambda_2) \dots \ r(\lambda_N)]^T$ is the vector of the sampled spectral reflectances of the scene. T is the transpose operator. From “(3)”, we first search to characterize the spectral response of the system, including the camera and the illuminant, by finding the operator $\mathbf{S}_k(\lambda)$. Then, using this operator, we reconstruct, from a multispectral image, the spectral reflectance curve for each pixel of the imaged scene (Mansouri et al).

Algorithm to Reconstruct Spectral Curve

Spectral reflectance curves reconstruction is an inverse problem; slight variations in input data completely skew the expected results. Mansouri, proposed a robust method based upon neural networks for “Asclepios” System, in order to overcome this problem by taking the advantage of robustness of neural network: associative memories against noise.

Mansouri modified the behavior of the perceptron to the probabilistic response by using the Boltzmann distribution. This option corresponds to the creation of associative memories which can be heteroassociative or auto associative. Heteroassociative memories associate a stimulus in the input to a response in the output even if the two vectors have not the same size, where auto associative memories associate a stimulus to itself and can, thusly be used to store stimuli. A statistical reason of using the probabilistic response is that, during the training, the perceptron may learn only few samples among possible stimuli. The memory stops learning when it ceases to mistake any more. So, it may place the discriminating function too much close to the boundaries of the samples with which it was trained. Now, in order to test on new samples coming from the same statistical population, the perceptron badly generalizes its training. In this way, as by using the delta rule known as Widrow-Hoff rule [10] in order to continuously modifying the strengths of the input connections to reduce the difference (the delta) between the expected output value e and the actual output o of a

neuron. This rule changes the connection weights in the way that minimizes the mean squared error of the neuron between an observed response o and a desired theoretical one like:

$$w_{ij}^{t+1} = w_{ij}^t + \eta(e_j - o_j)x_i = w_{ij}^t + \Delta w_{ij} \quad (4)$$

where e is the expected response, t is the number of iteration, and η is a learning rate.

For the given system lets, we acquire 10 mono-channel images with the hand held device. In order to construct the spectral volume with a step of lets X_{nm} in the range of 400 to 1000 nm, then the total number of values, we get at the output of the reconstruction process Y_{out} is computed with the formula for each pixel

$$Y_{out}(nm) = \frac{1000_{nm} - 400_{nm}}{X_{nm}}$$

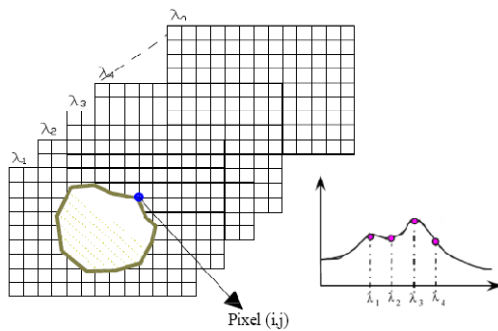


Figure13: Multispectral data volume, reconstructed for each pixel

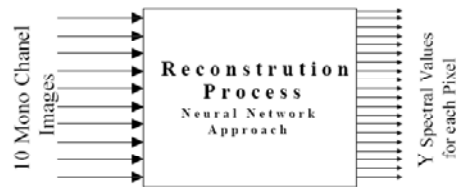


Figure 14: Schematic of Reconstruction Process from set of all images

4.3.2) Processing of Spectra Reconstructed (Plane by Plane Approach)

The plane by plane approach involves in analyzing the entire monochrome images from spectral volume individually (one plane at a time). Initially after getting the set of desire monochrome images, as described in previous section, all the images are analyzed, in order to detect the lesion.

The analysis of the images by using the plane by plane approach initially involves the automatic segmentation of monochrome images of skin lesions (Carrara et al). For each

multispectral image the detection is based on the Threshold reflectance Graph (TRG). The TRG from an image is calculated at each wavelength by plotting at each selected grey level the correspondent reflectance mean value of the entire pixel with a grey level smaller then the selected one. The thresholding of the image is automatically estimated by tuning into two manual parameters for each image. They represent the detection of the contour and internal isles of the lesion. After detecting the contour and lesion area the analysis proposed the best result (by comparing result of all wavelengths) for specific disease.

The approach is different from the currently existing methods, because it is a unique system which can gives result on any wavelength with in the range, in contrary to the existing one, which gave results on fewer fix number of wavelength. In conclusion the Asclepios would be the versatile combination of clinical dermoscopic rule (ABCD) and image processing techniques for multispectral images.

Chapter 5

Skin Segmentation Techniques

Skin cancers are the most common form of cancers in humans and can mainly be classified into melanoma and non-melanoma. Detection of malignant melanoma in its early stages not only reduces the mortality rate, but can also be helpful in reducing the considerable amount of financial expenses. Measurement of image features for the diagnosis of melanoma initially requires the detection and localization of lesion within the image. It is essential that lesion boundaries are determined accurately so that measurements can be accurately computed. For lesion boundaries, image segmentation is considered to be first step in many image analysis problems. In order to detect the skin infected area, many different approaches based on image segmentation technique have been proposed in the past. Some of them are explained in next section.

5.2) Overview of Segmentation Methods

Image segmentation is one of the most important steps of image analysis. The main goal is to separate the object from the background. Accurate color image segmentation has proved to be difficult and complex, especially when it comes to skin images, because of the variation in output medical devices and varying texture and color. Achieving adequate segmentation results depend mainly on techniques to detect uniformity among the feature values of the image points, and then isolating the uniform area. Several techniques have been developed. In general, image segmentation algorithms can be loosely categorized into thresholding methods, edge detection, and region oriented techniques.

5.2.1) Manual Tracing

Manual tracing of structural and lesion boundaries is the most basic of all segmentation techniques and is still quite commonly used in clinical and research settings. The operator manually traces the border of structures of interest on the computer screen. If the operator is skilled at recognizing tissue and lesion boundaries, this method is highly accurate, but this process becomes labor intensive, especially for radiologists whose expertise could be better applied elsewhere. One of the main goals of automated segmentation techniques is to free the operator from this manual task, and save considerable amount of time [28].

5.2.2) Thresholding

The simplest method of image segmentation involves thresholding. All pixels having a certain similar property e.g. given intensity range are classified as belonging to the same group. All pixels outside the given range are not included in the object. In most of the applications the main drawback in this approach is the difficulty in the proper selection of the threshold value required to optimally extract the desired objects e.g. many factors can affect the observed intensity value of an object in an image, such as, the characteristics of the imaged material, the proximity of an object to nearby objects, and imaging conditions (lighting, shadows). All these conditions combine to make it difficult to obtain an optimal threshold value [28]

5.2.3) Edge Detection

Edge detection methods involve in locating a significant change in intensity, which can most often be interpreted as edges between the objects. Although many improvements in edge detection have been demonstrated in recent years, the methods are still complicated by the difficulty of finding actual object boundaries, because of the presence of certain artifacts and noise e.g. hairs which results in the existence of several gaps along the detected contours [28].

5.2.4) Region Oriented Methods

Another class of image segmentation techniques is defined by the region-oriented methods. These techniques assume that objects are defined by individual, closed regions in space. Region analysis techniques are further broken down into region growing methods and region splitting and merging [28].

5.2.4.1) Region Growing

In region growing, a pixel or pixels in the image are used as a seed and an analysis is performed of the neighbors of the seed to determine inclusion into the region. This analysis is iteratively applied until the object ceases to grow further.

5.2.4.2) Split and Merge

The split and merge methods of region analysis work by iteratively splitting the image into smaller and smaller regions until it is determined that the resulting regions have some uniform property. The results of the image splitting are then merged with one another if it is determined that the merged regions also satisfy the desired property. The difficulty of defining the uniformity property and the complexity of applying these techniques detract from their general application.

5.3) Segmentation Parameters for Skin Modelling

Image segmentation algorithms extract regions on the basis of similarity of a predefined image feature such as gray-level value. In many applications, images that exhibit a variety of structure or texture cannot be adequately segmented by gray-level values alone. Additional features related to the structure of the image are needed to segment such images. Images of skin lesions exhibit significant variations in color hues as well as geometrical appearance of

local surface structure. For example, images of cutaneous malignant melanoma exhibit a rich combination of color and geometrical structure of pigmentation. Numerous techniques for color or shape modeling and recognition of skin lesion have been proposed during several past years. In the following section few techniques based on different approaches are briefly explained.

5.3.1) Color Spaces used for Skin Modelling

Skin color has proven to be a useful and robust cue for face detection, localization and tracking. Image content filtering, content aware video compression and image color balancing applications can also benefit from automatic detection of skin in images. Similarly, skin tumor may be distinguished from surrounding skin by features such as color, brightness or luminance, texture and shape. The use of color as a means to identify the tumor border is of particular importance, since in some cases, it is difficult to identify the tumor border in a monochrome image [29].

5.3.1.1) RGB

RGB is one of the most widely used color space for processing and storing of digital image data. However, high correlation between channels, significant perceptual non-uniformity, mixing of chrominance and luminance data make RGB not a very favorable choice for color analysis and color based recognition algorithms. Numerous techniques for RGB color modeling and recognition have been proposed during several past years.

Proposed Techniques

Ganster et al propose a multiple thresholding along with the 3D clustering based technique for the segmentation of color images [30]. **Lim and Lee** presente Fuzzy C- means clustering technique which uses coarse to fine concept to reduce the computational time as well [31]. **Schmid and Fischer** propose a technique based on Lim and Lee approach by using nearest

neighbor criteria for clustering. Their approach is based on two dimensional histogram analysis [32]. **Z. She et al** propose a method to generate shape of the lesion by using multiple scale ellipses and low pass filtering to smooth the boundaries; the texture is produced by using auto regressive models [33]. **Umbaugh et al** use two approaches for color image segmentation. The first is based on the spherical coordinate transform of original RGB data. The second is based on a mathematically optimal transform [34]. **Hand et al** present the border finding algorithm which initially involves a series of preprocessing steps to remove noise from the image, followed by color image segmentation, data reduction, object localization, and contour encoding. The border finding algorithm presented is based on the use of color as the basis for segmenting the tumor images into meaningful regions. Six different color segmentation algorithms are explored in this approach [35]. **Lee and Hsiao** present the wavelet transform based method to extract the region of the tumor from color medical image [36]. A simple RGB color model is used and in order to speed up the processing time, the RGB value of each pixel is mapped to an intensity value [36]. **Round, Duller and Fish** describe a region based approach to the segmentation of lesion images into the areas of differing color. The process initially divides the image into the rectangular regions small enough to be considered as having only a single color. This is then followed by conservative merging process. The optimal merging criteria is based on this computation of distances and it stops when the best possible merge has a distance which exceeds a threshold but is interrupted by the “cleaning” [37]. **Phung et al** use the Bayesian classifier with the histogram technique to present that that skin segmentation based on color pixel classification is largely unaffected by the choice of the color space [49]. **Gejgus, Placek and Sperka** present a skin-color method to segment skin-color areas in the image sequence. This method is robust to the various skin colors of different human races [50].

5.3.1.2) Normalized RGB

The image segmentation is actually the pixels clustering in the color space. Because almost all color space models contain three color vectors, it is time-consuming, complicate and difficult to calculate by utilizing three-color vector of the color space. Normalized RGB is

reducing the dimensions of color vectors that are easily obtained from the RGB values by a simple normalization procedure [29]:

$$r = \frac{R}{R+G+B} \quad g = \frac{G}{R+G+B} \quad b = \frac{B}{R+G+B}$$

A remarkable property of this representation is that for matte surfaces, while ignoring ambient light normalized RGB is invariant (under certain assumptions) to changes of surface orientation relatively to the light source [29].

Proposed Techniques

Tomaz, Candeias and shahbazkia use Mahalanobis distance as a similarity feature in human skin segmentation in one of the approach. The same authors propose another approach for skin segmentation only based in each pixel colour information, to determine its class. This requires initially camera calibration to determine the space that is considered as the colour of interest [38].

5.3.1.3) Hue, Saturation and Intensity

Hue-saturation based color spaces specify the color properties numerically. *Hue* defines the dominant color (such as red, green, purple and yellow) of an area; *saturation* measures the colorfulness of an area in proportion to its brightness. The ‘intensity’ is related to the color luminance. The following relation is most commonly used to compute the respective values of Hue, Saturation and Intensity [29].

$$\begin{aligned} H &= \arccos \frac{\frac{1}{2}((R-G) + (R-B))}{\sqrt{((R-G)^2 + (R-B)(G-B))}} \\ S &= 1 - 3 \frac{\min(R, G, B)}{R+G+B} \\ V &= \frac{1}{3}(R+G+B) \end{aligned}$$

Proposed Techniques

Shang et al propose a way of reducing dimensions of feature parameter in the segmentation of color skin erythema images by introducing a new segmentation feature parameter [39]. **Xua et al** propose an automatic method for segmentation of intensity images of skin cancer and other pigmented lesions, based on intensity thresholding. Double thresholding is used to focus on an image area where a lesion boundary potentially exists. Image edges are then used to localize the boundary in that area [40]. Similarly, **Galda et al** present a color clustering method that determines the number of colors automatically. First the RGB image is transformed into the LUV color space and segmented by a self-organizing map [41].

5.3.1.4) Y Cb Cr

YCbCr or Y'CbCr is a family of color spaces used in video and digital photography systems. Y' is the luma component and Cb and Cr are the blue and red chroma components. Color is represented by luma (which is luminance, computed from nonlinear RGB), constructed as a weighted sum of the RGB values, and two color difference values Cr and Cb that are formed by subtracting luma from RGB red and blue components [29].

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ C_r &= R - Y \\ C_b &= B - Y \end{aligned}$$

Proposed Techniques

Alberto, Luis and Edward present color map based, an unsupervised segmentation technique to divide skin detected pixels into a set of homogeneous regions by using the YCbCr color space [42].

5.3.2) Model Based Approach

The final goal of skin color detection is to build a decision rule that will discriminate between skin interest and non interest region. This is usually accomplished by introducing a

metric, which measures distance (in general sense) of the pixel values of two regions. The type of this metric is defined by the skin color modeling method [29].

Proposed Techniques

Ruiz del solar and Verschae propose a robust skin segmentation approach that uses multiple thresholding and neighborhood information [45]. **Oana et al** use the multi view textons-based representation of skin appearance. The histogram of image textons is used to encode the global distribution of the local structural attribute over the texture image. The 3D texture recognition method consists of training, and classification task [46]. **Dhawan and Sicsu** use gray-level intensity and texture-based features for region extraction. The intensity-based segmentation is obtained using the modified pyramid-based region extraction algorithm whereas the texture-based segmentation is obtained by a bi-level shifted-window processing algorithm that uses new generalized co-occurrence matrices [47]s. **Zhu, Qin and Zhou** introduce the physics concepts of kinetic and potential energy into image processing. Energy transformation is performed to map the pixels from the grayscale space into energy space [48]. **Gasparini and Schettini** propose Iterative Self-Organizing Data Analysis Technique (ISODATA) which is one of the classification-based, unsupervised learning Technique, for skin segmentation [51]. **Jianbo et al** evaluate several segmentation techniques for their effectiveness in distinguishing lesion from background in dermatoscopic images of pigmented lesions (moles and melanomas). This includes five techniques previously used for segmentation of pigmented lesions, and several new techniques based on stabilized inverse diffusion equations (SIDE) and Markov random fields (MRF) which produce the most accurate segmentations [53]. **Yasuaki et al** describe a set of fully automated algorithms that is specialized for analyzing a three-dimensional optical coherence tomography volume of human skin [54]. **Yuchun** proposes a model-based region segmentation algorithm in colour images. [55].

5.3.3) Multi Spectral Approach

Multi-spectral imaging can capture light from frequencies beyond the visible light range, such as infrared. This can allow extraction of additional information that the human eye fails to capture with its receptors for red, green and blue. For the accurate reproduction of the original color through digital imaging systems, the multispectral imaging technology is promising. By using the spectral information, the reproduced color accuracy is considerably improved as compared to conventional RGB-based systems. Moreover, the quantitative spectral information can be employed for the analysis or the information retrieval from the image database. Multispectral imaging technology has been applied to dermatology mainly for the diagnosis of melanomas and so far there exists only few techniques which are based on this approach for the detection of skin cancer.

Proposed Techniques

Tomaz et al evaluate the performance of a new spectroscopic system in the diagnosis of melanoma by a multispectral imaging system [43]. The lesion segmentation is obtained with the hybrid algorithm combining a region-oriented and a thresholding method, called region growing by pixel aggregation method. Data reduction techniques were applied before setting up a neural network classifier designed to perform automated diagnosis [43]. **Carrara et al** propose an automatic method for the segmentation of images of skin cancer and other pigmented lesions based on multispectral images. This method first reduces a color image into an intensity image and approximately segments the image by intensity thresholding. Double thresholding is used to focus on an image area where a lesion boundary potentially exists [44]. **Tomatis et al** propose the similar technique for the detection of skin lesion in multispectral images. The proposed technique is based on machine learning based classification algorithms [56]. Similarly, **Farina et al** proposed a technique to diagnose cutaneous melanoma from multispectral images. They proposed an automatic segmentation algorithm based on five different descriptors. These descriptors represent the color and shape of the lesion. The choice of these descriptors is made by taking into account some of the

lesion feature. Furthermore, the evaluation of these descriptors is made on different wavelengths [57].

This chapter presents the state of the art of several segmentation algorithms based on color and multispectral approach for the diagnosis of skin cancer in dermatological images. Although encouraging, but still the response of the instruments based on these approaches cannot currently replace the well established diagnostic procedures. However with the availability of advanced optical filters, which can tune the wavelength, the way for spectral high resolution imaging is opened. This results in giving the information, which is not visible even to human eye e.g. spectrally, eyes are not sensitive to see for example the haemoglobin absorption peaks around 540 nm and thus are not that well suited to discriminate between oxygenated and de-oxygenated blood. However, currently there are only few systems which are based on multispectral approach; there still exist a need to test already implemented algorithms on multispectral images. Among the several proposed algorithm for color images, the algorithm proposed by Hand et al has the strong potential to test on multispectral images. His boarder finding algorithm is based on region based segmentation technique. Similarly region detection technique proposed by Round et al can also be applied on multispectral images. Tomaz et al used Mahalanobis distance for color images; it can also be applied on multispectral images.

Chapter 6

Methodology for Skin Segmentation

The current primary method for detecting melanoma relies on the visual assessment of the skin to interpret whether a pigmented skin lesion is suspicious for melanoma or not. But this fact shows that this method is based highly on the experience and ability of the dermatologist to recognize patterns using clinical examination. However, many particular aspects of the skin can not be evaluated effectively with the naked eye but are clearly delineated by imaging methods. Many attempts have been made to automate the detection of melanoma from the digital color and surface reflectance images. Those attempts initially involve the segmentation of the skin lesion from the surrounding skin followed by the calculation of classification features. Accurate description and measurement of image features cannot be achieved without accurate image segmentation. Therefore, a wide range of algorithms have been proposed in the past for color image segmentation

In this chapter, we describe the implementation and evaluate the efficiency of algorithms dealing with the issue of segmentation for multispectral images containing skin lesions, proposed by Carrara et al. The procedure mainly concern with the isolation of skin lesions from the surrounding healthy skin.

6.1) Image Acquisition

The set of multispectral skin images used for the assessment were acquired with the hand held device containing monochrome camera and a set of 10 filters. The device is connected with the PC with 8MB high speed fire wire. The xenon Light source with light spectrum in

the range of 380nm to 1000nm produced the set of 10 images with the help of 10 transmittance filter in the same range.

In order to avoid the reflection of light source and to ensure the reproducibility of the images uniform lighting conditions along with the software corrections were applied to the images. All the acquired monochrome images are size of 2 octets, 1280 x 960 pixels, where later reduced to 640 x 480 pixels, in order to reduce computational cost. At the same time all the multispectral images are cropped from the boarder to avoid the high reflection of light, which significantly effect the interested area and also in some data set the hairs around the the lesion area were shaved off before acquisition, in order to avoid the interference during reflectance measurement. Image analysis algorithm explained in coming few section is geneated in the Matlab Programming enviroment.

6.2) Software Corrections

Initially in order to reduce the effects of noise, all the images were filtered out. Median filter is used as a correction tool for reducing noise e.g. Hairs, scales etc. The median filter considers each pixel in the image in turn and looks at its nearby neighbours to decide whether or not it is representative of its surroundings. Although this procedure ends in relatively blurring of the image, but it assists the segmentation procedure. Similarly as the wavelength of the acquired images are getting higher, the relative contrast between the skin and lesion area is reduced, therefore in order to avoid this, images has also been manually adjusted .

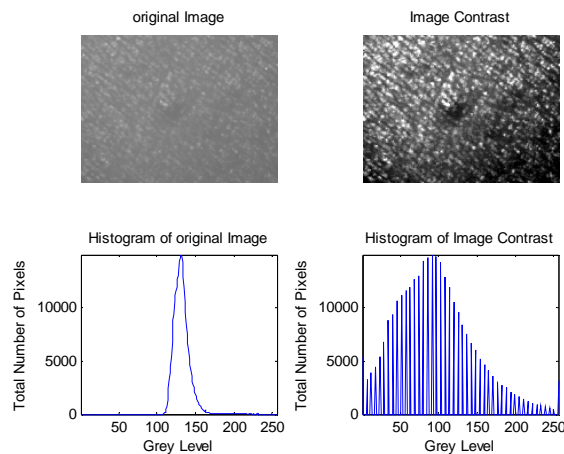


Figure 15: a) Original Image; b) Image Contrast

Approximately we had applied software corrections on all the images, except in reconstructed spectra, where some images are well contrast and does not required extra

correction. In results section while explaining the images we have explained about the affect of software correction on different images as well. In the next section we, describe the segmentation process of an image containing a cutaneous disease, which involves in the separation of the skin lesion from the healthy skin.

6.3) Image segmentation

Automated image segmentation is one of the most difficult tasks in image analysis; especially, in the field of dermatology due to the complex nature of skin. At the same time this procedure should be performed very accurately in order to avoid the improper extraction of the lesion features.

Image segmentation algorithm implemented is achieved by the combination of following two different approaches:

- (i) Region Growing.
- (ii) Thresholding Techniques.

6.3.1) Region Growing

In this approach we group the pixels or sub regions into larger regions. Initially Starting with a set of 'seed' pixel, this procedure groups pixels into larger regions by appending connected neighboring pixels having similar properties (e.g. intensity). In skin lesion images where the color differences are intense this technique gave better results and end up in a compact boundary around lesion area.

6.3.2) Thresholding

Thresholding is also one of the simplest approaches for the segmentation process; this is based on the fact that the values of pixels that belong to a skin lesion differ from the values of the background. Therefore, this technique separate the lesion from its background by initially finding the proper threshold for every monochrome image and then later separate the lesion by giving different numerical value to the lesion and its background. In our case

we have generated a binary mask based on these approach where 1 represent the area where lesion is present and 0 correspond to the background or part of the skin. More accurate segmentations will result with highly contrasted objects; therefore for higher wavelength we manually make the image contrast

6.4) Algorithm Steps

Based on the combination of the two different approaches explained in previous section, the segmentation method developed for skin lesions is composed of following steps.

6.4.1) Image Windowing: Step 1

Initially the image is divided into the regions of 10×10 pixels. After computing the mean intensity of each region, the darkest pixel inside the darkest region is then fixed as the ‘seed’ of the searched region.

6.4.2) Seed Generation: Step 2

Starting from the seed, all connected pixels with intensity smaller than a determined threshold value (explained in next section) are appended, by considered that as the part of the region and ‘1’ is placed to the segmentation mask. All the pixels with the intensity greater than threshold is added to the segmentation mask as the part of the background or skin area, and 0 is placed for that part.

6.4.3) TRG Generation: Step 3

In implemented approach, the method to find the threshold is not based on the grey-level histogram but on a representation of the monochrome image termed as Threshold-Reflectance Graph (TRG).

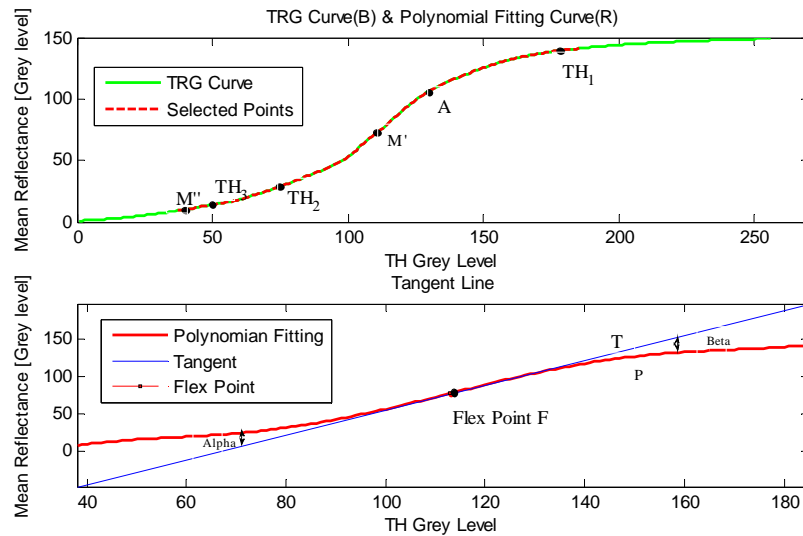


Figure 16: a) TRG Curve; b) Polynomial Fitting 'p' and Tangent line 't' through Flex Point F

6.4.3.1 Threshold-Reflectance Graph (TRG)

The TRG from the monochrome image is calculated at each wavelength by plotting at each selected grey level (x -axis) the correspondent reflectance mean value (y -axis) of all pixels with a grey level smaller than the selected one. Each grey level is considered a likely threshold value and for each of this value the related segmentation mask and the mean intensity of the pixels inside the mask are evaluated. The TRG curve (Figure 16) can be divided into four main segments.

Region 1:

From 255 to TH_1 , the TRG curve is nearly constant or very slowly varying, because there exist only few pixels whose value lies inside this specific range. Furthermore the differences between skin and lesion are still not recognizable in this region.

Region 2:

The region between TH_1 and TH_2 correspond to the transition from skin to lesion. The curve becomes steeper because there exist relatively large number of pixels having intensity TH, and by reducing TH greatly reduces the mean value of the remaining pixels. Therefore, reducing TH in this range further reduce the size of the segmentation mask. M' is the value of TH where the curve shows the maximum gradient.

Region 3:

From TH_2 to TH_3 , the slope of the curve decreases and the values of TH are entering into the range of the lesion pigmentation. The TRG is relatively less steep in this range therefore, fewer pixels are eliminated by reducing TH and ultimately, the smaller are the changes in the outline by diminishing TH.

Region 4:

From TH_3 to M'' , the gradient of the curve again increases due to the fact that the reduction of TH in this grey-level range excludes an increasing fraction of pixels and greatly reduces the size of the segmented region inside the lesion.

6.4.4) Polynomial Fitting: Step 4

Between the selected area (M' and M'') of the TRG is fitted by a third-order polynomial function p (only in few cases its 5)), and the most deviating point is computed in the whole curve. That deviating point is termed as the flex point F. The tangent line t to this flex point F is drawn and then later evaluated for the selection of threshold value.

6.4.5) Threshold Computation: Step 5

For every monochrome image, after fixing the α value within the range given below, the algorithm automatically determine the threshold value TH_{λ}^* in the surroundings of TH_2 , which defines the region where the lesion pigmentation in TRG starts. The threshold TH_{λ}^* for the segmentation of the entire lesion must satisfy the following conditions:

$$\begin{aligned} p(TH_{\lambda}^*) &> t(TH_{\lambda}^*) + \alpha \\ p(TH_{\lambda}^* - 1) &< t(TH_{\lambda}^* - 1) + \alpha \\ \alpha &\in [0.5-1.5]. \end{aligned} \tag{1}$$

Similarly TH_{λ}^{**} is in the surroundings of TH_3 , which represents the segmentation threshold of the dark islands inside the lesion and can be evaluated at each wavelength. The dark represent the area whose value is further lower then threshold, which varies from case to case. The threshold TH_{λ}^{**} for the segmentation of the dark islands should satisfy the following conditions:

$$\begin{aligned} p(TH_{\lambda}^{**}) &< t(TH_{\lambda}^{**}) - \beta \\ p(TH_{\lambda}^{**} + 1) &> t(TH_{\lambda}^{**} + 1) - \beta \\ \beta &\in [0.5-1.5]. \end{aligned} \tag{2}$$

The parameters α and β determine the fine tuning of the segmented boundary of lesion and dark island, respectively.

6.4.6) Region Growing: Step 6

After computing the value of threshold by following above criteria, we generated the binary image. The two threshold value depicts the detection of boundary of the pigment and internal islands. The region growing algorithm starts from the seed generated in step 2 and then check all its neighboring pixels for the given threshold values (Figure 17). At the end

binary image was generated for each monochrome image and for all the images of spectral volume.

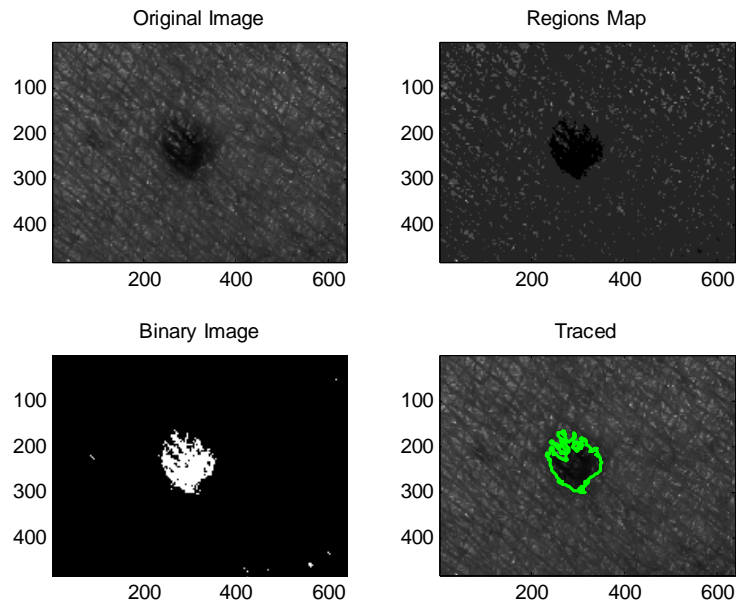


Figure 17: a) Original Image; b) Region Map of the Image; c) Binary Image ; d) contour detection of Binary Image

The contour of the lesion is generated by boundary generation algorithm in Matlab. The algorithm has been tested on different type of images which includes RGB images as well. The result of the algorithm on different data set is explained in next chapter.

Chapter 7

Results

In this chapter we present the results of the algorithm presented in the last chapters. The Algorithm has been tested on three different types of Data set, which are explained in detail in next coming section.

7.1) Threshold Reflectance Graph

The threshold reflectance graph detects the threshold value in order to generate binary image from all the given data set. The change in the threshold value at different points (Figure 18a), directly effects the segmented area of the lesion detected. In next subsection we explain in detail that how the change in the value of threshold in different range affect the segmentation results.

7.1.1) Threshold Value between A TH₁:

This area has relatively less steeper slope and if the threshold value is selected in this area, which contains mainly the background pixel, results in giving abrupt region, which contains a lot of skin surface as shown in Figure 18b. In the given monochrome images, due to the presence of light reflection, which further brighten the whole images, the threshold value selected in this area gave worse results especially in case of higher wavelengths (630nm onwards)

7.1.2) Threshold Value at M'

M' is the most deviation point in the whole curve; it depicts the starting region of lesion where curve is entering from normal skin region to defected area in the image. We draw the

tangent line through this point and then by adjusting the two parameters individually for all the images, we got the segmentation mask of the lesion, as shown in Figure 18c. In this figure, even the lesion boundaries, where the disease is although not centralized but still its effect is there and the area of the skin is affected because of the specific pathological situation.

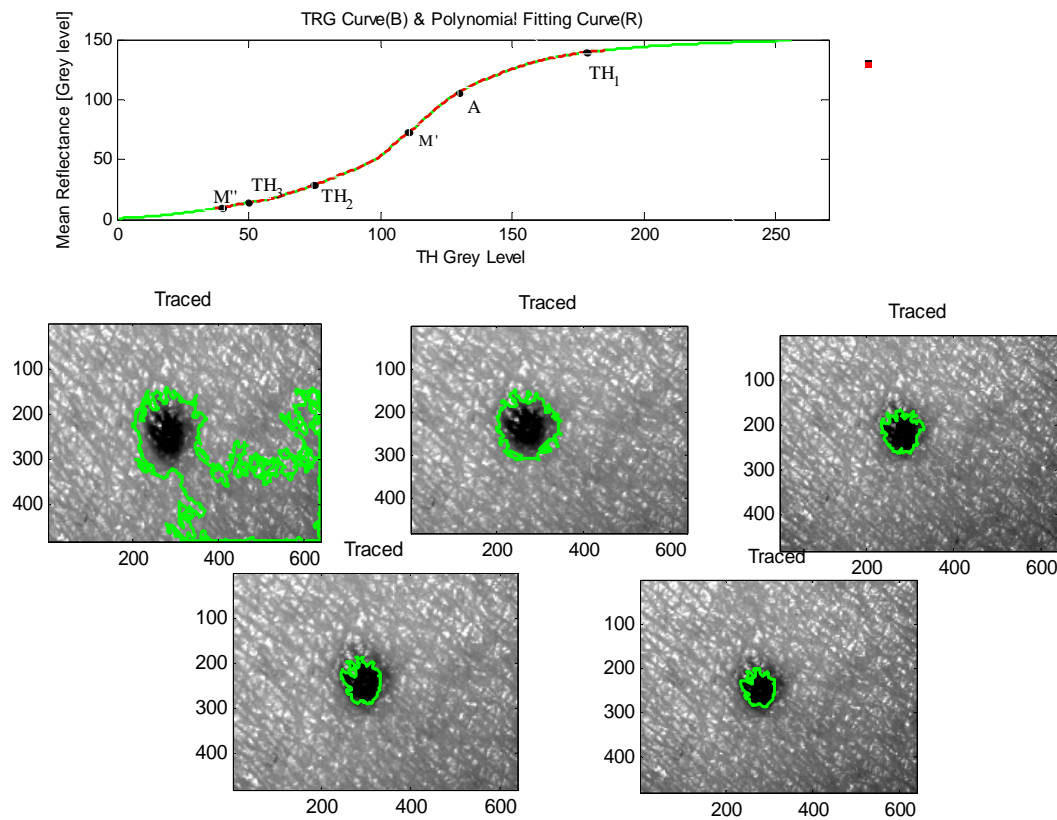


Figure 18: a) at TRG Curve at 610nm ; b) Segmentation result at 'A' ; c) segmentation result at M'; d) segmentation result at TH₂; e) Segmentation result at TH₃; f) Segmentation result at M''

7.1.3) Threshold Value at TH₂

Further reducing the threshold value, results in giving tight boundary around the exact position of the lesion as shown in Figure 18d. At this threshold the algorithm gave the best results in the wavelength range of 550 to 670nm. The monochrome images are neither highly contrasted and neither too much brighten. So, for given data set in most of the images, the results are quite encouraging (shown in next section).

7.1.4) Threshold Value at TH_3

The threshold value in this range results in giving wrong boundary in case of the whole lesion because the actually lesion has covered more area than the detected one, but this range is considered to be as for the detection for the internal islands, and in the given figure, the segmentation result in giving one dense island as shown in Figure 18e.

7.1.5) Threshold Value at M''

This is the lowest possible value for the threshold value for the given Monochrome image. At this value we got the results of detecting exact small islands. But unfortunately for the given image, we had only one dominant island, so, for this threshold hold value, the segmentation algorithm gave nearly the same result as in last threshold value. At this value the size of the segmentation region reduce considerably and results in giving the concentrated dark island region.

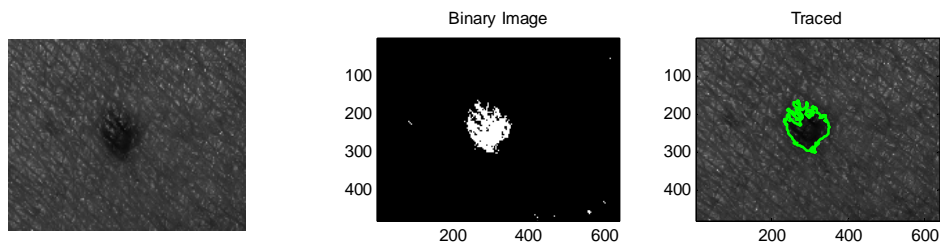
7.2) Segmentation Results On Monochrome Images

In this section, we explain the results on the monochrome images taken in the range of 400nm to 1000nm. All the images were taken, after shaving off the hairs near the effected area, which ultimately results in reducing the noise, but at the same time increased in the reflection on the surface of the skin, as human skin is the semi transparent, shiny surface with the fine scaled texture.

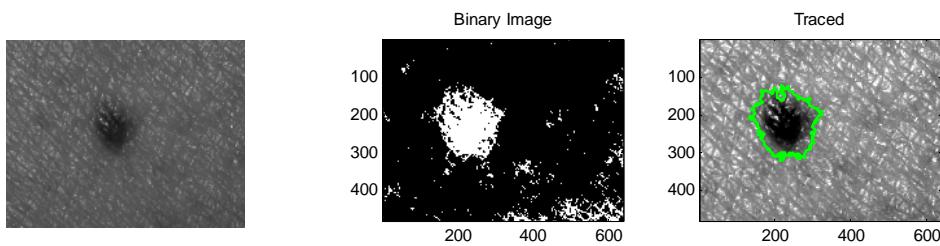
The results of the segmentation algorithm for all the monochrome images on different wavelengths are shown below, For the given pathology relatively on smaller wavelength, the algorithm gave good results in case of detecting the whole lesion, as can be seen from the results shown below, with the increase in the wavelength the segmentation area is also decreasing, this is due to the increase in the brightness, with the increase in the brightness the color contrast between the lesion and skin is reducing and secondly as due to the significant light reflection the lesion became almost of the same color as the background in

the case of highest wavelength , which ultimately results in giving a very small area. The problem of light reflection has been tried to overcome by adjusting the image, but it result in giving relatively bad results in some cases, because it results in the boosting of the reflection around the lesion as well. The higher wavelengths are found to be better for the detection of dark islands.

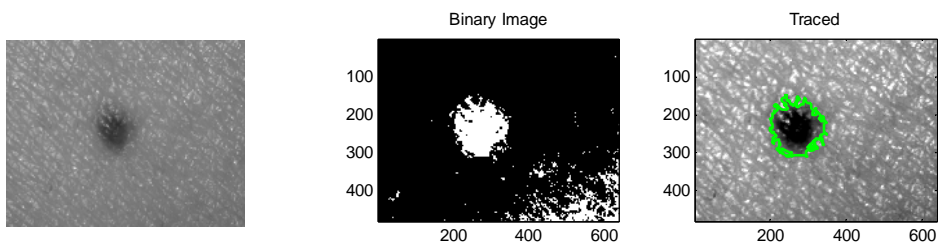
i) wave length = 430 nm



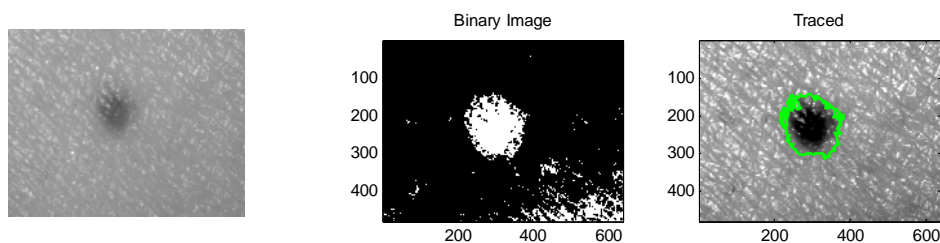
ii) wave length = 490 nm



iii) wave length = 550 nm



iv) wave length = 610 nm



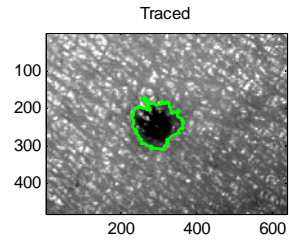
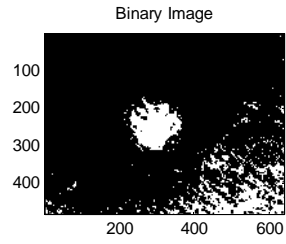
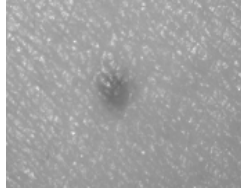
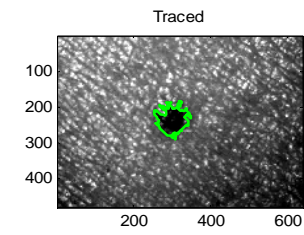
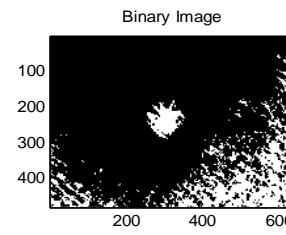
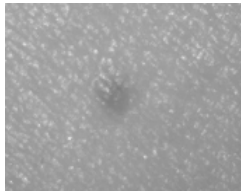
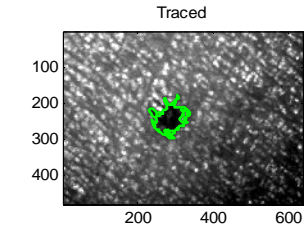
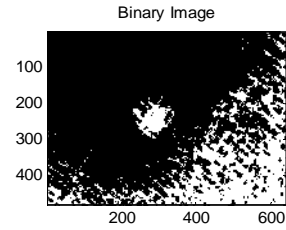
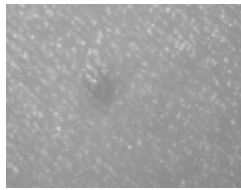
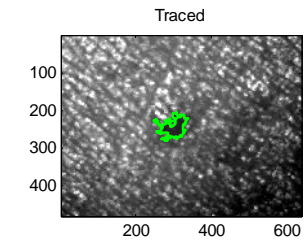
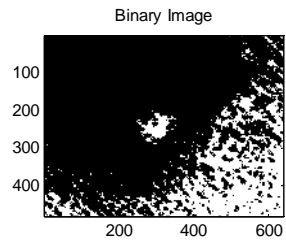
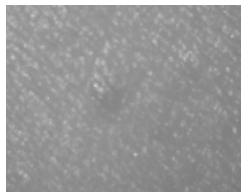
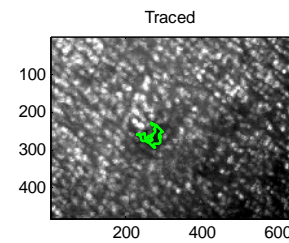
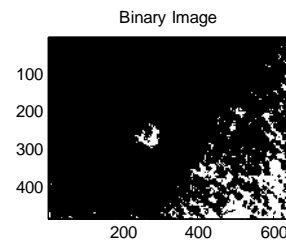
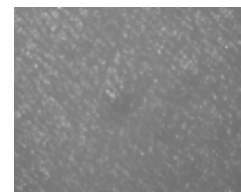
v) wave length = 670 nm**vi) wave length = 730 nm****vii) wave length = 790 nm****viii) wave length = 850 nm****ix) wave length = 910 nm**

Figure 19) Segmentation results on different wavelengths on monochrome images.

The variation in the lesion area with wavelength is mainly due to the fact that as the wavelength increases images of benign lesions become fade and as, since roundness and

border irregularity are related to the spatial resolution of the lesion outline, the less faded the images the more the details would be the lesion outline.

7.3) Segmentation Results On Noisy Monochrome Images

The same segmentation algorithm is then applied to the different data set having hairy monochrome images. The images taken on the same wavelengths as in the last case. If we compare the results of both of the data set, in this case, on smaller wavelength, the algorithm is detecting hairs as the part of the lesion, due to the dark color of the hair, and also because as on smaller wavelength the image is relatively darker, and if the lesion is also extremely dark, then its better not to do image adjustment for making contrast, but in this case we don't do it, then black color is ofcourse darkest one, therefore logically algoitham is working correctly. The algorithm in this type of data sets is highly dependent on the nature of the skin of patient, because normally people with fair color has brown or light color hair as compared to the people with dark complexion ; having dark, in some cases black hairs.

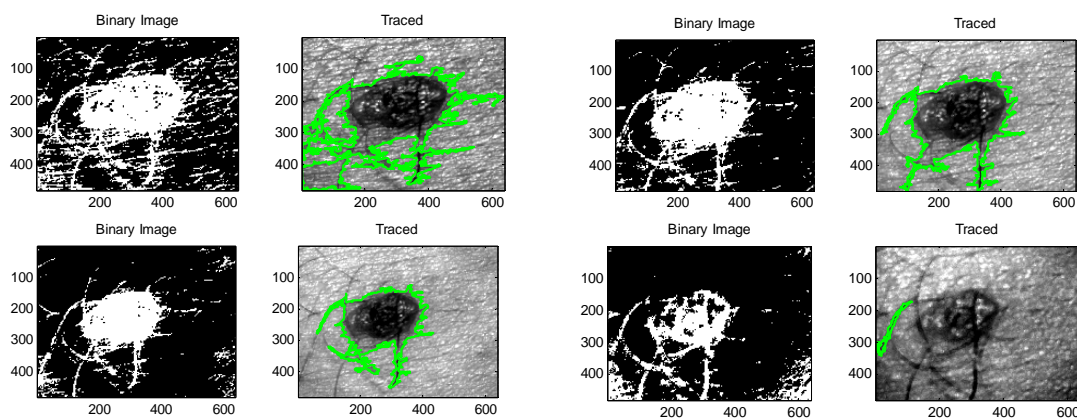


Figure 20) Segmentation results on Noisy Images at the wavelength of : a) 430nm, b) 490nm, c) 550nm, d) 910nm

Similary if the data set is like in our case, then it is worse to diagnose on higher wavelength, because just like in last dataset, on higher wavelength the image contrast is very less, even on highest wavelength its difficult to judge with naked eye that from where, the leision is starting. Therefore in order to overcome this problem, we have proposed the image

adjustment technique, but for this type of data set this worse, because instead of boosting the lesion, it results in boosting more the hairs around the lesion and as a result , the algorithm detects the hair as the area of interest. Therefore, for this type of dataset, the results are much better in the case of relatively lower wavelengths. The results on four different monochrome images at different wavelength are shown in Figure 20, where smaller wavelength gave the best result. The optimum wavelength found in our case is the range of 480 to 590nm.

7.4) Segmentation Results On RGB Images

We have tested our algorithm on Luminance parameter of RGB images. The luminance property of the RGB images are extracted by using Matlab function and then the same procedure has been applied on these images as applied in previous two datasets. The TRG curves of all the images were fitted with either 3 or 5 degree of polynomial. The results shown in Figure 21 were got at TH_1 value of the respective images.

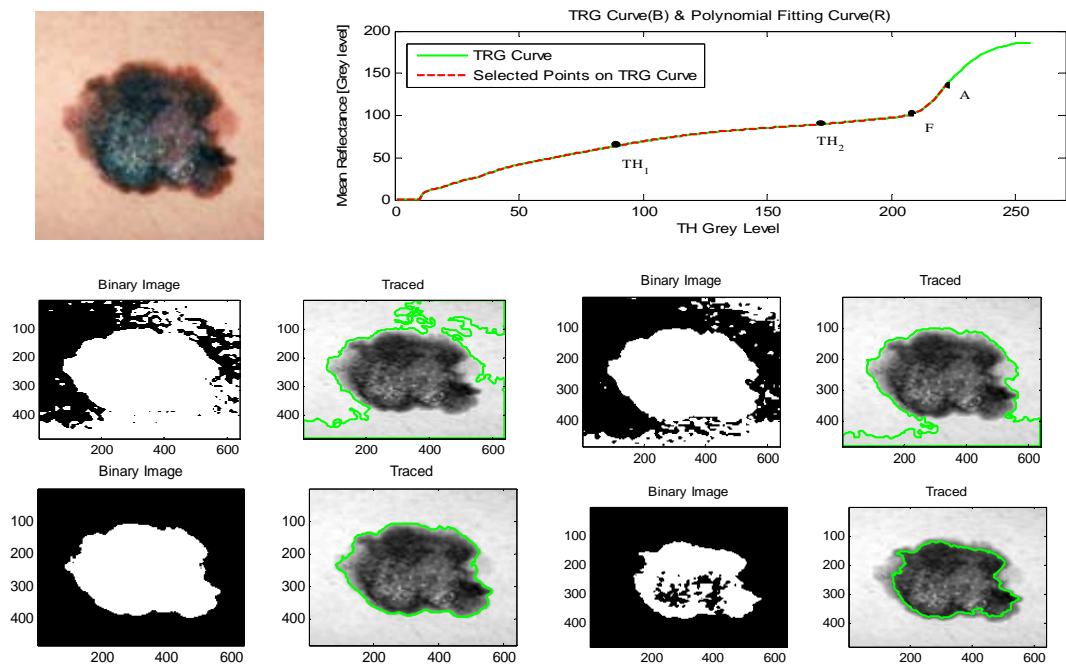


Figure 21: a) Original Image ; b) TRG Curve of Luminance Image ; c) Segmentation result at 'A' ; d) Segmentation result at F; e) Segmentation result at TH_2 ; f) Segmentation result at TH_3

Nearly in some of these Images, the algorithm successfully detects the lesion, but it's not always the same. In the case of Figure 21, although the lesion is detected but at the same time algorithm has detected some safe area of the skin as the part of the lesion. This is due to that fact that the threshold has been applied at point A, which is higher threshold then the flex point. If, we further lower the threshold value, it results in giving accurate segmentation at nearly TH_2 . Further lowering of threshold value results in giving less area and in fact missed some internal dark island as well (Figure 21f)

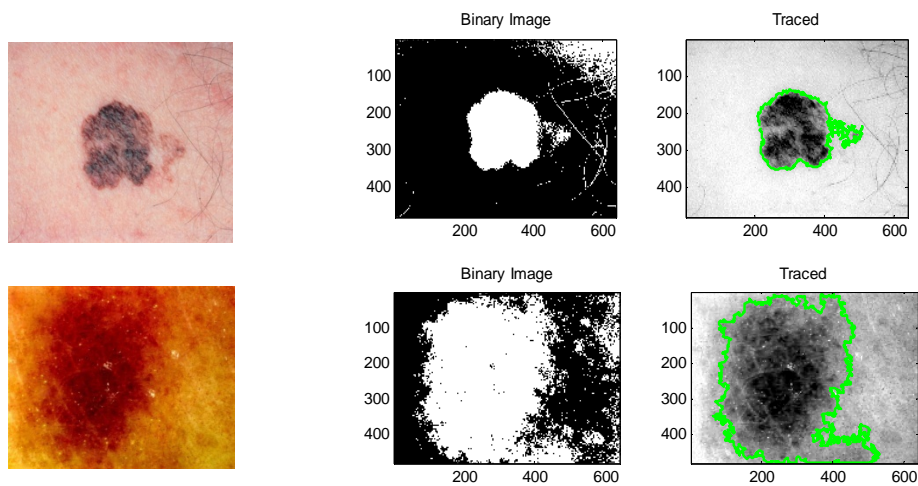


Figure 22) Segmentation results on the Luminance Parameter of Different RGB Images

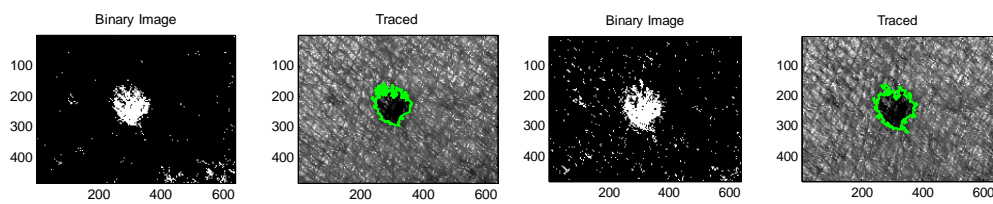
Similarly in the case of Figure 22, approximately correct detection of the lesion has been done, apart from some error; the algorithm detects the boundary of the lesion. In the case of first image, there also exist some of the noise, hairs, but still the lesion boundary has been detected very clearly, which is however different in the case of b, where although boundary has been detected but also some unaffected area has also been detected as the part of lesion.

7.5) Segmentation Results On Spectral Reconstructed Volume

Finally we had applied our segmentation algorithm on the reconstructed volume. We had acquired total of 60 images with the step of 10nm, within the range of 400nm to 1000nm. The results obtained are given below in Figure 23. The segmentation algorithm worked relatively better on the reconstructed images, as compared to the monochrome

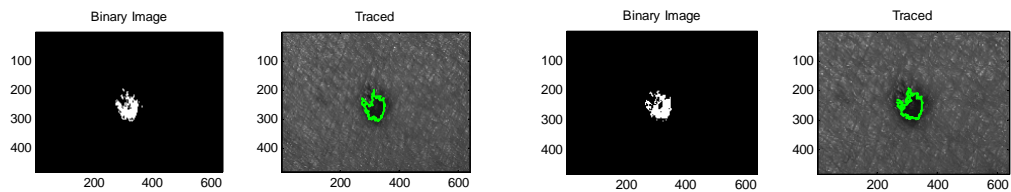
images acquired directly from the camera. This is due to the fact that, the reconstructed algorithm tries to reduce the effect of reflection. At lower wavelength between the range of 400 to 480nm, the algorithm successfully contour the lesion, but it consider the noise as well as part of lesion. We had applied image adjustment because on these wavelength, as the whole image is highly dark, and there is very less contrast.

i) wave length = 420nm & 430nm

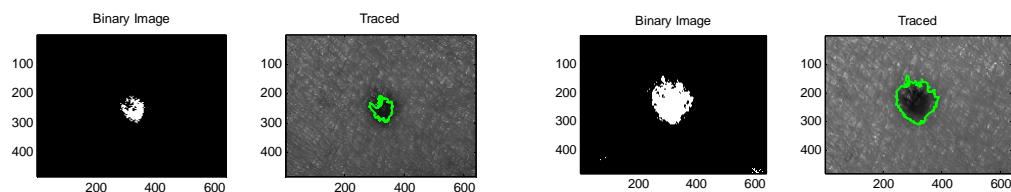


The segmentation algorithm applied in the range of 490nm to 510nm, results in giving internal islands quite well and also some part of the lesion boundary, In this range, we didn't applied image contrast technique, because images in this range are highly uniform and gave best results as can be seen in the figures below.

ii) wave length = 490nm & 500nm



iii) wave length = 510nm & 620nm

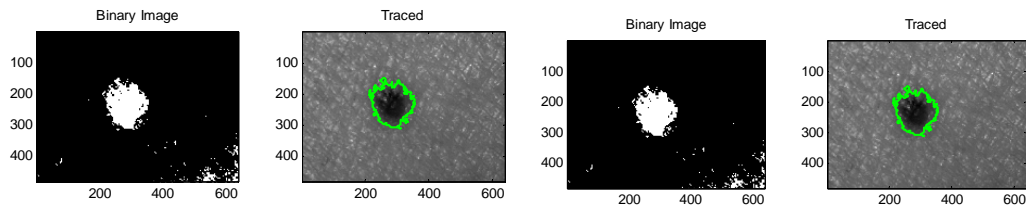


Seg

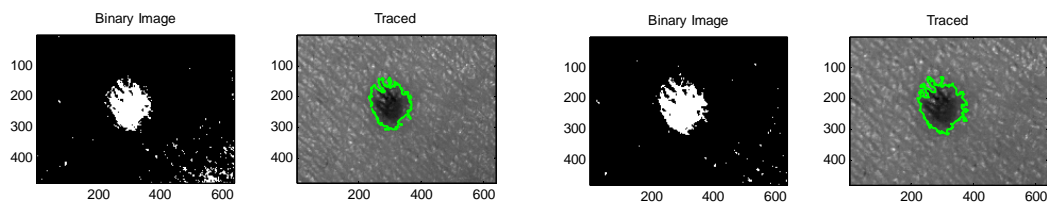
mentation algorithm applied in the range of 510nm to 660nm works quite well, especially

for the detection of lesion boundary, in this range as well, the images were uniformly contrast and same as in last case, and we didn't apply image adjustment techniques.

iv) wave length = 630nm & 640nm

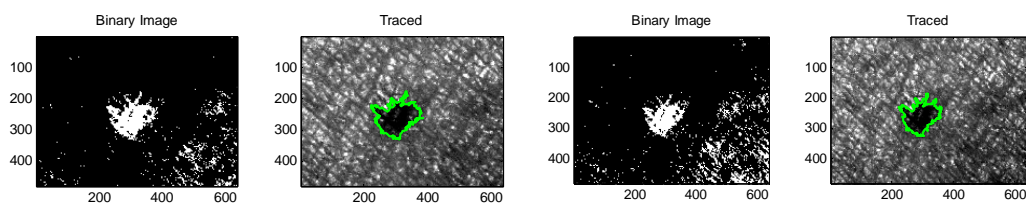


v) wave length = 650nm & 660nm



Images obtained from the reconstructed volume in the range of 700nm onwards are relatively fade and results in giving poorer contrast with the increase in wavelength, therefore without image adjustment it was not possible to detect lesion, and therefore we manually generate the image contrast. After applying these software correction techniques, the algorithm successfully works, but at the same time, it results in boosting the noise parameter as well, as in the images below, the noise around the lesion is highest as compared to other range.

vi) wave length = 860nm & 870nm



vii) wave length = 880nm

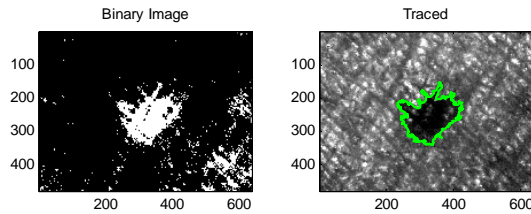


Figure 23) Segmentation results by applying to Spectral Volume on different images within the range of 400nm to 1000nm

In conclusion, our algorithm works quite well on most of the images, and we suggest that in order to detect the lesion, the images acquired in the range of 480nm to 670nm gave the best results for both the detection of boundary of the lesions and dark islands. Besides that in this range, the images are quite well uniform and does not required any further software correction, as we did in the case of lower and higher wavelengths. However, we have applied our algorithm on limited dataset and pathology and it is more likely in the case of skin pathologies that severity of the lesion varies in size from one to the others, therefore we propose a work in future to test this algorithm on large dataset, in order to make sure the detection with in the same range.

Conclusion

In the previous sections, we have explained about our system, about the image processing techniques implemented for the diagnosis of skin pathologies and finally we have presented the results we obtained from our system and algorithm. The segmentation method implemented is quite effective to diagnose skin lesion, especially in the case of multispectral images. The threshold computing technique, which is based on the Reflectance Graph for each monochrome image, came out to be quite effective and allowed the detection of either boundary of the whole lesion or even internal island. The primarily results obtained were quite encouraging, in most of the cases our method worked successfully. Not only on the acquired monochrome images, but also the result acquired by testing on the Luminance parameter of RGB images were also encouraging. The segmentation algorithm on each plan gives more information than on the 10 acquired images. Moreover, the comparison of the results on the plans can be an interesting help for diagnostic, e.g. an area segmented at 500 nm twice than the area segmented at 700 nm can bring pertinent information.

In most of the imaging based computer assisted system, while implementation special consideration is given to the specific pathology, which however is not correct, because different kind of skin pathology have different characteristics .we have tried to develop the system to work for most of the type of such pathologies. So far, the image processing technique based on Carrara et al method of automatic segmentation of malignant melanoma, has been tested on different type of data set and it works quite well on them. However, as in future work we proposed to implement another approach to contour check the results obtained, and we are quite hopeful that in the end, with the fusion of these two approaches the **‘Asclepios System’** results in giving reliable global diagnose for any type of skin pathology.

Future Work

In this thesis report, we have presented a technique to automatically segment the skin pathologies in monochrome images, acquired with the different filters. At the same time, we had applied our algorithm on reconstructed spectra by using plane by plane approach. In plane by plane approach, we had analyzed the entire monochrome images from spectral volume individually (one plane at a time). Initially after getting the set of desire monochrome images from the spectral reconstruction, we had applied segmentation algorithm on each plane of the spectral volume and at the end we had suggested the appropriate wavelength for the diagnosis of the given specific pathology. In the segmentation method, we have used some image processing tools to overcome the problem of light uniformity, however, from the results, as we have explained in previous chapter, with the increase in the wavelength , the software correction results, in boosting of light as well which however significantly affect the detection process. Therefore, we propose in future work to make sure the uniform distribution of light on the captured area e.g. by using polarized sensors or to use some other image processing based noise removal techniques. In terms of segmentation algorithm, in chapter 5 we have proposed some algorithm for the segmentation RGB images, but they can also be tested for multispectral image segmentation. Therefore, we also propose in future work to test those algorithms on the images acquired from Asclepios System.

In this thesis report we were limited to the only one type of pathology, therefore we can not claim that, the algorithm will work as accurately for other type of pathologies as well. We propose in future work to test this algorithm on large dataset having different pathologies and also with different skin colours.

The scope of this thesis is limited to the plane by plane approach, however, we propose another method for the reconstruction of spectra and analyzing of the monochrome images, by signal processing techniques e.g. in depth approach. The broad concept of in depth approach is explained with the help of figure 24. In in-depth approach, after getting the spectral reconstruction, we analyze the skin for each pixel by taking one pixel spectrum at a time. It means that for each pixel we had let's set of 60 reconstructed values, and we generate the reflectance curve for each of these pixels and with the differencing in these curves, we can evaluate the area.

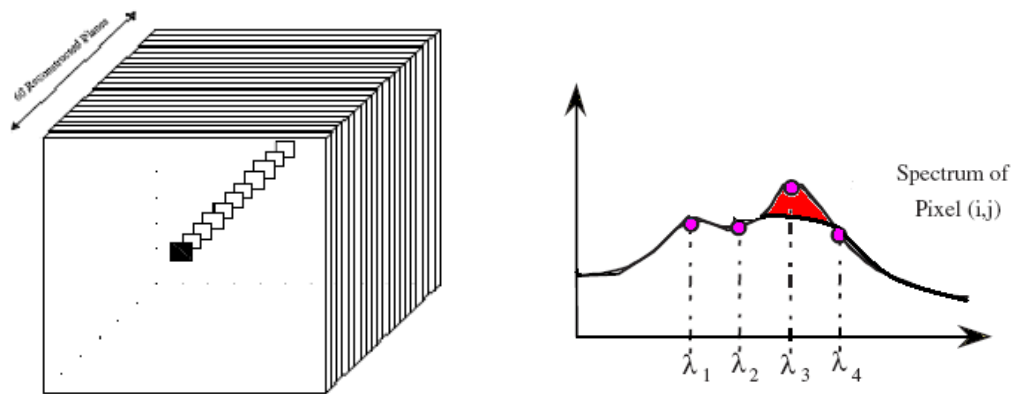


Figure24: a) Spectral reconstruction by in depth Approach b) Fusion of two approaches

In Future work, we also propose the implementation of this approach, and at the end with the fusion of these two ways, we can better give one global diagnostics for the given pathologies.

References

- [1] Diane M. Thiboutot , “Dermatological Applications of High-Frequency Ultrasound “,
Section of Dermatology, The Pennsylvania State University College of Medicine, Hershey,
PA 17033
- [2] M. Marozas, R. Jurkonis”Review on skin lesion imaging, analysis and automatic
classification “, Biomedical Engineering Institute, Kaunas University of Technology
- [3] Schuco International , Dealer Catalogue , 3rd sept 2007
- [4] K. C. Nischal, Uday Khopkar , “Dermoscope”,Department of Dermatology, Seth GS
Medical College & KEM Hospital, Parel, Mumbai - 400012, India
- [5] Ashfaq A. Marghoob, md,a,_ lucinda d. Swindle, md,a,_ claudia z. M. Moricz,”instruments
and new technologies for the in vivo diagnosis of melanoma”, j am acad dermatol november
2003, New york
- [6] Monika-Hildegard Schmid-Wendtner, MD; Walter Burgdorf, MD ,“ Ultrasound Scanning
In Dermatology”,Arch Dermatol. 2005;141:217-224.
- [8] Robert W. Coatney, “Ultrasound Imaging: Principles and Applications in Rodent
Research”, Department of Laboratory Animal Sciences, GlaxoSmithKline, King of Prussia,
Pennsylvania.
- [9] S. Camilla, M. Daniela , C. Alessio , S. Marcello, C. Pietro, F. Paolo and C. Paolo,
“Application of optical coherence tomography in non-invasive characterization of skin
vascular lesions” , Department of Dermatology, University of Florence,and Department
of Human Pathology and Oncology, University of Florence, Florence, Italy

- [10] F.M. Hendriks , “chanical Behaviour of Human Skin in Vivo , Nat.Lab, July 2001
- [11] Moganty R Rajeswari, Aklank Jain, Ashok Sharma, Dinesh Singh, N R Jagannathan, Uma Sharma and M N Degaonkar “Evaluation of Skin Tumors by Magnetic Resonance Imaging
- [12] “Safety Guidelines for Conducting Magnetic Resonance Imaging (MRI) Experiments Involving Human Subjects Center for Functional Magnetic Resonance Imaging”, University of California, san Diego , July 2007
- [13] “A Primer on Medical Device Interactions with Magnetic Resonance Imaging Systems” , CDRH Magnetic Resonance Working Group, February 7, 1997
- [14] Misri Rachita, Pande Sushil, Khopkar Uday, ‘Confocal laser microscope’, Department of Dermatology, Sent GS Medical College and KEM Hospital, Parel, Mumbai
- [15] Nana Rezai, “Confocal Microscopy - A Visual Slice of the Cellular world”, The science creative Quarterly
- [16] <http://www.fotofinder.de/en/dermoscopy.html>
- [17] <http://www.isis-optronics.de/en/skindex/produkte/content.html>
- [18] Episcan® I-200 Dermal Ultrasound Scanner , www.mediluxprofessional.net
- [19] M. Moncrieff, S.Cotton, E.Claridge and P. Hall, “Spectrophotometric Intracutaneous Analysis: a new technique for imaging pigmented skin lesions”, British Journal of Dermatology 2002; 146: 448–457.
- [20] <http://www.astronclinica.com/technology/siascopy-explained.htm>
- [21] <http://www.eosciences.com/>
- [22] “Spectrophotometric analysis of skin lesions”, DermNet NZ, Dec 2007
- [23] P. Hans, A. Guiseppe ,H. Rainer and Robert H. Johr, “Color Atlas of Melanocytic Lesions of the Skin”, septembre 2007
- [24] <http://www.lucid-tech.com/medical-imagers/vivascope-1500.asp>
- [25] P.wilhelm , B. Enzo, E. Peter, I. Maibach, “Bio Engineering of Skin: Skin Imaging and

Analysis”, *Dermatology: Basic science series*.

- [26] M Lualdi, A Colombo, M Carrara, L Scienza, S Tomatis and R Marchesini, “Optical Devices Used For Image Analysis Of Pigmented Skin Lesions: A Proposal For Quality Assurance Protocol Using Tissue-Like Phantoms”, *Institute Of Physics , Publishing*, 15 November 2006
- [27] Mansouri et al ,”Neural Networks in Two Cascade Algorithms for Spectral Reflectance Reconstruction” , *Le2i, UMR CNRS 5158, UFR Sc. & Tech., University of Burgundy*
- [28] Brian Gerard Johnston, “Three-Dimensional Multispectral Stochastic Image Segmentation” *Memorial University Of Newfoundland, Cabot Institute Of Technology*, January 1994
- [29] Vladimir V, Vassili .S, Alla A, “A Survey on Pixel-Based Skin Color Detection Techniques”, *Graphics and Media Laboratory ,Moscow State University,Moscow, Russia*.
- [30] Harald Ganster*, A. Pinz, R. Röhner, E . Wildling,M. Binder, And H. Kittler, “Correspondence Automated Melanoma Recognition” , *IEEE Transactions On Medical Imaging*, Vol. 20, No. 3, March 2001
- [31] Y. Won Lim and S. Uk Lee , “On the color image segmentation algorithm based on the thresholding and the fuzzy c-means techniques “ , *Department of Control and Instrumentation Engineering, Seoul National University*, February 1989.
- [32] Ph. Schmid and S. Fischer, “Colour Segmentation For The Analysis Of Pigmented Skin Lesions” *Signal Processing Laboratory, Swiss Federal Institute of Technology, 1015 Lausanne, Switzerland*
- [33] Z. She, P.J.Fish and A.W.G.Duller, “ Simulation Of Optical Skin Lesion Images” , *University of Wales, Bangor, Conexant Digital Infotainment, Castlegate, Tower Hill, Bristol, , U.K.*
- [34] S. E. Umbaugh,R H. Moss,W.V. Stoecker,G A. Hance, “Automatic Color Segmentation Algorithms With Application to Skin Tumor feature Identification”, *IEEE Engineering In Medicine And Biology*, September 1993.
- [35] G. A. Hand, S. E. Umbaugh,R H. Moss, and W Y. Stoeck, “ Un supervised Color Image Segmentation, with application to skin tumour boarder”, *IEEE Engineering In Medicine And Biology*, January/February 1996
- [36] J.Der Lee and Yu-Lin Hsiao , “Extraction of Tumor Region in Color Images Using Wavelets” , *Chang Gung University , Taiwan January 2000 ,An International Journalcomputers & mathematics with applications*

- [37] A., J. Round, A. W. G. Duller and P. .J. Fish , “ Colour Segmentation For Lesion Classification”, IEEE/EMBS Oct. 30 - Nov. 2, 1997 Chicago, IL. USA
- [38] F. Tomaz, T. Candeias and H. Shahbazzkia, “Fast and accurate skin segmentation in color Images”, Proceedings of the First Canadian Conference on Computer and Robot Vision (CRV’04)
- [39] KeKe Shang, Liu Ying, Niu Hai-jing and Liu Yu-fu,” Method of Reducing Dimensions of Segmentation Feature parameter Applied to Skin Erythema Image Segmentation”, Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005
- [40] L. Xua, M. Jackowski, A. Goshtasby, D. Roseman, S. Bines, C. Yu, A. Dhawan, A. Huntley, “ Segmentation of skin cancer images” , Image and Vision Computing 17 (1999) 65–74.
- [41] Galda H, Murao H, Tamaki H and Kitamura S , “ Skin Image Segmentation Using a Self Organizing Map and Genetic Algorithms” , Transactions of the Institute of Electrical Engineers of Japan. 2003.
- [42] Alberto A, Luis T And, Edward J. D, “An Unsupervised Color Image Segmentation Algorithm For Face Detection Applications” , Politechnic University Of Valencia, Politechnic University Of Catalonia, Spain
- [43] Stefano T et al “Automated Melanoma Detection With A Novel Multispectral Imaging System: Results Of A Prospective Study” ,Institute Of Physics Publishing Physics In Medicine And Biology, 30 March 2005
- [44] Mauro C et al, “Automated Segmentation Of Pigmented Skin Lesions In Multispectral Imaging “ , Institute Of Physics Publishing Physics In Medicine And Biology Phys. Med. Biol. 50 (2005) N345–N357 , November 2005
- [45] J Ruiz-Del-Solar And Rodrigo Verschae , Robust Skin Segmentation Using Neighborhood Information, Dept. Of Electrical Engineering, Universidad De Chile, Santiago, Chile
- [46] Oana G. Cula Kristin J. Dana, “Image-based Skin Analysis” , CS Department ECE Department, Rutgers University, Texture 2002 - 1 and 2 June 2002, Copenhagen (co-located with ECCV 2002)

-
- [47] Dhawan AP, Sicsu A , “Segmentation of images of skin lesions using color and texture information of surface pigmentation”, Department of Electrical and Computer Engineering, University of Cincinnati, OH 45221.
- [48] Liangen Zhu, Shiyin Qin, and Fugen Zhou ,”Skin image segmentation based on energy transformation” , Journal of Biomedical Optics -- March 2004 -- Volume 9, Issue 2, pp. 362-366
- [49] S Lam Phung, A Bouzerdoum And D Chai,” Skin Segmentation Using Color Pixel Classification: Analysis And Comparison”, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 27, No. 1, January 2005
- [50] P. Gejgus, J. Placek and M. Sperka, “Skin color segmentation method based on mixture of Gaussians and its application in Learning System for Finger Alphabet”, International Conference on Computer Systems and Technologies - CompSysTech’2004
- [51] F. Gasparini, R. Schettini , “,Skin segmentation using multiple thresholding” Universita degli Studi di Milano bicocca, Milano Italy
- [52] Ilias Maglogiannis, “Automated Segmentation and Registration of Dermatological Images”, Journal of Mathematical Modelling and Algorithms 2: 277–294, 2003.
- [53] Jianbo G, Jun Z, Matthew G. Fleming, Ilya P, A B. Cagnetta , “Segmentation of dermatoscopic Images by Stabilized Inverse Diffusion Equations”, 1998 IEEE
- [54] Yasuaki H, Yoshiaki Y, Shingo S, Masayuki M, Tomoko S, Violeta D M, Masahiro Y, Shuichi M, Takeshi Y, Tsutomu A, “Automatic characterization and segmentation of human skin using three- dimensional optical coherence tomography”, Optical Society of America, 2006
- [55] Yuchun Fang Tieniu Tan, “A Novel Adaptive Colour Segmentation Algorithm and Its Application to Skin Detection, National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, China
- [56] Stefano Tomatis et al, “Automated melanoma detection with a novel multispectral imaging system: results of a prospective study” Institute Of Physics Publishing, 30 March 2005
- [57] B Farina et al,” Multispectral imaging approach in the diagnosis of cutaneous melanoma: potentiality and limits”, Phys. Med. Biol. 45 (2000) 1243–1254, January 2000