

Automatic Detection and Segmentation of Skin Melanoma Images- An Introduction

Gurkirat Kaur, Kirti Joshi

Department of Computer Science & Engg,
RIMT (IET) Mandi-Gobindgarh, India

Abstract-

Melanoma is a cancerous lesion in the pigment-bearing basal layers of the epidermis and is the most deadly form of skin cancer, yet it is also the most treatable, with a cure rate for early-stage melanoma of almost 100%. Therefore, there is a need to develop computer-aided diagnostic systems to facilitate the early detection of melanoma. The first step in these systems is skin lesion segmentation. The next essential step is feature extraction and pattern analysis procedures to make a diagnosis. According to the literature, pigment network or reticular pattern is an important diagnostic parameter for melanoma. We decided to work on this automatic melanoma detection system. In this paper, an introduction is given about different characteristics of the melanoma cancer images and a brief review has been present in which different features of melanoma have been discussed. Finally a survey has been given which carry out the analysis of melanoma images by different methods.

Keywords: UVB, UVA, EFIS,

I. INTRODUCTION

Skin cancer is considered as the most common form of cancer worldwide. The incidence is considerably increasing. For example in the US, at current rates, a skin cancer will develop in one in five people during their lifetime [1]. Skin cancers can be classified into two major groups which are melanoma and non-melanoma skin cancers. These type of skin cancer (non-melanoma) is usually start in the basal cells or squamous cells. Such cells are found at the base of the outer layer of the skin. Approximately 1,200,000 non- melanoma skin cancers develop in the US. The Exposure of the skin to sunlight is considered as the main factor behind the development of the most basal and squamous cellcancers. Basal cell or squamous cell cancers can be cured if found and treated early. Melanoma is the most dangerous type of skin cancer. The World Health Organization approximates that more than 70230 people a year in the world die from too much sun, mostly from malignant skin cancer [2]. Early detection of this cancer can help its curability. Melanoma arises from the cancerous growth in the pigmented spots. Dermatologists can diagnose melanoma in about 80% of cases according to ABCD process [3]. Digital dermatoscopy could give dermatologists a closer look at suspicious skin lesions. This, in turn, can help dermatologists to find suspicious lesions in an early step. To measure and detect sets of features from dermoscopic images, the computerized analysis of these images can be extremely useful and helpful for dermatologists in order to facilitate their diagnosis. Based on images obtained by digital dermatoscopy, our conclusive aim is to develop an aided-diagnostic system for the identification of early stage melanomas. This would enable supervised classification of melanocytic lesions. The melanoma detection process is composed of five steps that are the preprocessing, the segmentation, the post-processing, the feature extraction and finally the classification .

II. CAUSES OF MELANOMA

Sun exposure, in the form of UVB and UVA light, is a potential cause of melanoma. Evidence suggests that several episodes of sunburn due to intense, intermittent sun exposure significantly increase the risk of developing a melanoma later in life [4]. There is emerging evidence that exposure to ultraviolet radiation through the use of sun beds also increases the risk of melanoma. In 2009, the International Agency for Research on Cancer raised the classification of ultraviolet-emitting tanning devices to “carcinogenic to humans” in the highest-risk category . This is based on evidence that people who regularly use sun beds have a substantially higher risk of developing cutaneous melanoma. The most recent meta-analysis concluded that the use of sun beds increases the risk of melanoma by 75%, especially when used before the age of 35 [5]. Ultraviolet radiation appears to induce melanoma through many mechanisms, including suppression of the immune system of the skin, induction of melanocyte cell division and free radical production. Free radicals are highly reactive molecules that are produced in the body naturally as a byproduct of metabolism, and as a result of exposure to toxins in the environment such as tobacco smoke and ultraviolet light. Free radicals contain an unpaired electron. In essence, they are in a constant search to bind with another electron to stabilize themselves – a process that can damage DNA and other parts of human cells. This damage may play a role in the development of cancer and other diseases, as well as accelerating the ageing process [6].

III. SIGNS OF MELANOMA CANCER

Major signs

- Change in size – the mole may become lumpy or spread outwards over the skin

- Change in shape – most moles have a smooth, regular outline, but a melanoma is more likely to have an irregular, ragged edge
 - Change in colour – the mole may develop a reddish edge. It may become darker or appear to have different shades of colour, usually a mixture of brown and black.
 - Melanomas can also be red, due to inflammation, or have a blue-white tinge due to partial clearing in the centre.
- Minor signs
- Diameter – most normal moles are smaller than the blunt end of a pencil (7mm)
 - Inflammation – many early melanomas are inflamed or have a reddish edge
 - Crusting or bleeding – slight oozing is a common symptom and causes the melanoma to stick to clothing
 - Sensory change – itching

Automated system for detection and localization

Early work on automated systems to assess the risk of melanoma used dermoscopy images. These are images that are obtained via a digital dermoscope, which is a device that assists dermatologists by magnifying surface detail and filtering surface reflectance. However, only 48% of practicing dermatologists in the U.S. use dermoscopes, so the proposed automated systems are difficult to widely adopt. Recent systems use images taken by a standard digital camera, which is more accessible to dermatologists. The photographs are segmented to identify the lesion area, features are extracted from the lesion, and the lesion is classified in terms of risk of melanoma. The problem is that illumination from skin surface reflectance impacts all three of those steps. For example, in Fig. 1, illumination changes across the photographs horizontally or vertically.



Fig. 1: Examples of illumination variation in skin lesion images

In image (a), the illumination variation changes horizontally, while in image (b), it changes vertically. As a result, healthy skin areas obstructed by shadows appear similar in color as the skin lesion, which results in misclassification of those areas. Illumination correction is an important preprocessing step for skin lesion photographs prior to segmentation and classification algorithms. Many illumination correction algorithms exist, but they are not designed specifically for skin lesion photographs. Common algorithms correct for illumination based on histogram equalization or the illumination–reflectance model. Histogram equalization adjusts the distribution of pixel intensities and minimizes illumination variation on a global scale [7]. However, this method does not take into account or correct for local illumination variation. The illumination–reflectance model assumes a multiplicative relationship between illumination and reflectance. Algorithms take advantage of this model by estimating the low-frequency illumination component and use it to find the reflectance component. The difference between the algorithms is the initial illumination estimation. One of the earliest algorithms that use the illumination–reflectance model is the retinex algorithm, which estimates illumination by applying a set of Gaussian filters of different sizes to the image. Other approaches include using morphological operators, bilateral filters, Monte Carlo sampling, or total variation to estimate illumination. Below is a brief literature review of some of the existed work in similar type of segmentation.

IV. LITERATURE SURVEY

Below is a description of few segmentation techniques used regarding the topic.

Jeffrey Glaister and David A. Clausiet *al.* [1] has compared his segmentation results on melanoma skin cancer images using joint statistical texture distinctiveness with those results obtained from other state-of-art algorithms. They have shown that their results have higher segmentation accuracy as compared to all other tested algorithms.

Ahmed A. Othman, Hamid R. Tizhoosh, [2] Member, IEEE, and FarzadKhalvatiet *al.* [10] proposed the formation and evolution of fuzzy rules for user-oriented environments in which feedback is captured by design. The evolving fuzzy image segmentation (EFIS) can be used to adjust the parameters of existing segmentation methods, switch between their results, or fuse their results. Specifically, they proposed a single-parametric EFIS (SEFIS), apply its rule evolution to breast ultrasound images, and evaluated the results using three segmentation methods, namely, global thresholding, region growing, and statistical region merging. Their results show increased accuracy across all tests and for all methods.

SitiNorainiSulaiman and Nor Ashidi Mat Isa *et al.* [3] proposed a new clustering algorithm called Adaptive Fuzzy-K-means clustering for image segmentation which could be applied on general images and/or specific images captured using different consumer electronic products. The algorithm employs the concepts of fuzziness and belongingness to provide a better and more adaptive clustering process as compared to several conventional clustering algorithms. Both qualitative and quantitative analyses favor the proposed AFKM algorithm in terms of providing a better segmentation performance for various types of images and various number of segmented regions. Based on the results obtained, the proposed algorithm gives better visual quality as compared to several other clustering methods.

KoushikMondal *et al.* [4] proposed a fuzzy rule guided novel technique that is functional devoid of any external intervention during execution. Experimental results suggest that this approach is an efficient one in comparison to different other techniques extensively addressed in literature. In order to justify the supremacy of performance of our proposed technique in respect of its competitors, we take recourse to effective metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Peak Signal to Noise Ratio (PSNR).

GrigoryBegelma and Michael Rudzsky *et al.* [5] demonstrated the usage of fuzzy classification engine in nuclei cell segmentation. The fuzzy rules were based on shape and color features. Classification engine was set up with statistically estimated distribution parameters of image features and verified on a large microscope image data set. The fuzzy method exhibited better segmentation results then segmentation based on crisp rules.

Gandini S *et al* [6] A systematic revision of the literature was conducted in order to undertake a comprehensive meta-analysis of all published observational studies on melanoma. An extensive analysis of the inconsistencies and variability in the estimates was performed to provide some clues about its Epidemiology. Following a systematic literature search, relative risks (RRs) for sun exposure were extracted from 57 studies published before September 2002. Intermittent sun exposure and sunburn history were shown to play considerable roles as risk factors for melanoma, whereas a high occupational sun exposure seemed to be inversely associated to melanoma.

Nilkamal S. Ramteke , Shweta V.Jain *al.*[7] This paper first reviews the past and present technologies for skin cancer detections along with their relevant tools. Then it goes on discussing briefly about features, advantages or drawbacks of each of them. Then we discuss the mathematics preliminary required to process the image of skin cancer lesion using our proposed scheme. This paper presents a new approach for Skin Cancer detection and analysis from given photograph of patient's cancer affected area, which can be used to automate the diagnosis and therapeutic treatment of skin cancer.

P. G. Cavalcanti and J. Scharcanski, *et al* [8] This paper describes a new method for classifying pigmented skin lesions as benign or malignant. The skin lesion images are acquired with standard cameras, and our method can be used in telemedicine by non-specialists. Each acquired image undergoes a sequence of processing steps, namely: (1) preprocessing, where shading effects are attenuated; (2) segmentation, where a 3-channel image representation is generated and later used to distinguish between lesion and healthy skin areas; (3) feature extraction, where a quantitative representation for the lesion area is generated; and (4) lesion classification, producing an estimate if the lesion is benign or malignant (melanoma).

V. CONCLUSION

According to the literature, pigment network or reticular pattern is an important diagnostic parameter for melanoma. Different literature work address the problem of how to determine the absence or presence of pigment networks in a given dermoscopic image. Some define it as a typical pigment network is which is light-to-dark brown in colour with small, uniformly spaced network holes and thin network lines distributed more or less regularly throughout the lesion and usually thinning out at the periphery. Most of the methods are robust, reliable, computer-aided diagnostic tool for analyzing the texture in lesions of the skin to detect pigment networks in the presence of other structures such as dots. All these methods have some drawbacks, in which methods are defined according to a particular feature of the melanoma image such as intensity, streaks and their regularity and non-regularity characteristics. Different methods used different methods for extraction of feature set as well as final classification in terms of present or absent of the melanoma cancer in the image.

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