COMPREHENSIVE STUDY ON IMAGE-BASED COMPUTER AIDED DETECTION OF SKIN MELANOMA CANCER - A SURVEY

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***Abstract*— The occurrence of malignant melanoma has been increasing worldwide. A well-organized non-invasive computer-aided diagnosis (CAD) is seen as a solution to make identification process faster, and accessible to a large population. Such automated system relies on three things: reliable lesion segmentation, pertinent features' extraction and good lesion classifier. Automated melanoma recognition in dermoscopy images is a very challenging task due to the low contrast of skin lesions, the huge intraclass variation of melanomas, the high degree of visual similarity between melanoma and non-melanoma lesions, and the existence of many artifacts in the image.**

***Index Terms*— Medical Image, Skin Cancer, Segmentation.**

I. INTRODUCTION

The anthropological skin is the prime part of the human body and covers about approximately 20 square foot area. The main role of the skin is to help the human body to regulate the temperature, protect the internal body parts from the ultraviolet rays, microbes and permits the sensations of touch, heat, and cold. There are three main layers of the human skin i.e. Epidermis, dermis and hypodermis.

Mainly there are two types of skin cancer lesions i.e. benign and malignant lesions. In benign lesions (common nevi) melanin deposits are normally found in the epidermis layer. In malignant lesions, melanin is reproducing at a high abnormal stage. Malignant lesions are not life threatening till the melanocytes and their associated melanin remains in the epidermis layer but when they penetrate into the dermis and leave deposits then the nature of the skin colour changes [1-3].

The most dangerous form of skin cancer, these cancerous growths develop when unrepaired DNA damage to skin cells (most often caused by ultraviolet radiation from sunshine or tanning beds) triggers mutations (genetic defects) that lead the skin cells to multiply rapidly and form malignant tumors. These tumors originate in the pigment-producing melanocytes in the basal layer of the epidermis. Melanomas often resemble moles; some develop from moles. The majority of melanomas are black or brown, but they can also be skin-colored, pink, red, purple, blue or white. Melanoma is caused mainly by intense, occasional UV exposure (frequently leading to sunburn), especially in those who are genetically predisposed to the disease. The figure 1 presents various examples of skin lesions, which as dysplastic nevus, seborrheic keratosis, melanoma and squamous cell carcinoma[4].

If melanoma is recognized and treated early, it is almost always curable, but if it is not, the cancer can advance and spread to other parts of the body, where it becomes hard to treat and can be fatal. While it is not the most common of the skin cancers, it causes the most deaths.

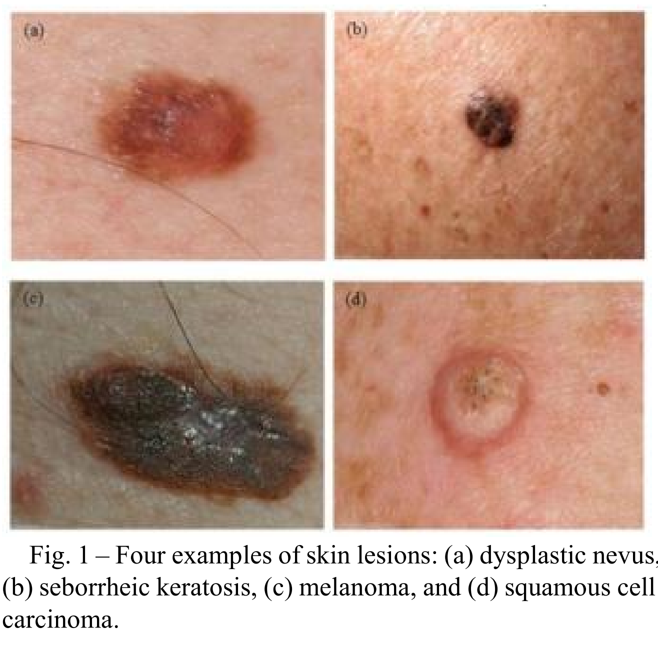

Fig. 1 – Four examples of skin lesions: (a) dysplastic nevus, (b) seborrheic keratosis, (c) melanoma, and (d) squamous cell carcinoma.

World wide there are so many human beings are affected with this cause[5-10]. Table 1 presents the survey report of skin cancer based on 1995-2015 incidence rates.

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Table 1 – Number of new cases of skin cancer, according to gender, in the USA, UK and Brazil.

Country	Type of skin cancer	Year	Number of new cases	
			Male	Female
USA[a]	Melanoma	2014	43,890	32,210
UK[b]	Melanoma	2010	6201	6617
	Non-melanoma		55,747	43,802
Brazil[c]	Melanoma	2014	2960	2930
	Non-melanoma		98,420	83,710

[a] Estimated number, based on 1995–2010 incidence rates.
[b] Confirmed cases in 2010.
[c] Estimated number in 2014 and valid also for 2015.

II. DATASET

For the study of melanoma detection, Authors performed extensive experiments to evaluate our method on a public challenge dataset of Skin Lesion Analysis Towards Melanoma Detection released with ISBI 2016. This dataset is based on the International Skin Imaging Collaboration (ISIC) Archive1, which is the largest publicly available collection of quality controlled dermoscopic images of skin lesions[32]. The challenge employs a subset of representative images with 900 images as training data and 350 images as testing data. The ground truth is held out by the organizer for independent evaluation. After releasing the challenge result, the organizer released the ground truth to encourage further investigations. In this case, we can perform extensive experiments to comprehensively evaluate our method [33,34].

Some datasets are publically available. The details of the dataset are as follows.

PH2: PH2 is publically available dermoscopic image database acquired Dermatology Service of Hospital Pedro Hispano, Matosinhos, Portugal. The PH2 dataset has been developed to facilitate comparative studies on melanoma segmentation and classification (Mendonca, Ferreira, Marques, Marcal, & Rozeira, 2013). PH2 dataset contains 200 images and available on http://www.fc.up.pt/addi/ph2database.html(PH2 Database, 2013).

DermIS and DermQuest: Melanoma image dataset is also available on DermIS and DermQuest Website. Dataset is freely available to use for educational purpose.

ISIC challenge dataset : The International Skin Imaging Collaboration (ISIC) is an international effort to improve melanoma diagnosis. This challenge provides dataset which is publically available. This dataset contains 900 images for the training purpose and 350 images are for the testing purpose[35].

III. IMAGE SEGMENTATION METHODS

Medical Image segmentation is a process, which subdivides an image region into its constituent regions or objects. The complexity level to which the subdivision is carried depends on the problem being solved. That is, medical image segmentation should stop when the objects of interest in an application have been isolated. For example, in the automated inspection of electronic assemblies, interest lies in analyzing images of the products with the objective of determining the presence or absence of specific anomalies, such as missing components or broken connection paths.

Segmentation of nontrivial images is one of the most difficult tasks in image processing. The accuracy of segmentation determines the intermediate success or failure of proposed methods / procedures. For this reason , considerable care should be taken to improve the probability of rugged segmentation. In some context , such as production inspection in a plant. The experienced image processing system designer invariably pays considerable attention to such opportunities. In other applications, such as autonomous target acquisition, the system designer has no control of the environment. Then the usual approach is to focus on selecting the types of sensors most likely to enhance the objects of interest while diminishing the contribution of irrelevant image detail[11-17].

Image segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity. In the first case, the approach is to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approaches in the second category are based on partitioning an image into regions that are similar according to a set of predefined criteria [18].

Several general-purpose algorithms and techniques have been developed for image segmentation. To be useful, these techniques must typically be combined with a domain's specific knowledge in order to effectively solve the domain's segmentation problems. The following are few standard generalized methods explained :

Thresholding :

Thresholding is the simplest non-contextual segmentation technique. With a single threshold, it transforms a greyscale or colour image into a binary image considered as a binary region map. The binary map contains two possibly disjoint regions, one of them containing pixels with input data values smaller than a threshold and another relating to the input values that are at or above the threshold. The former and latter regions are usually labelled with zero (0) and non-zero (1) labels, respectively. The segmentation depends on image property being thresholded and on how the threshold is chosen.

Generally, the non-contextual thresholding may involve two or more thresholds as well as produce more than two types of regions such that ranges of input image signals related to each region type are separated with thresholds. The question of thresholding is how to automatically determine the threshold value.

Simple Thresholding :

The most common image property to threshold is pixel grey level: $g(x,y) = 0$ if $f(x,y) < T$ and $g(x,y) = 1$ if $f(x,y) \geq T$, where T is the threshold. Using two thresholds, T1 < T1, a range of grey levels related to region 1 can be defined: g(x,y) = 0 if f(x,y) < T1 OR f(x,y) > T2 and g(x,y) = 1 if T1 ≤ f(x,y) ≤ T2.

A general approach to thresholding is based on assumption that images are multimodal, that is, different objects of interest relate to distinct peaks (or modes) of the 1D signal histogram. The thresholds have to optimally separate these peaks in spite of typical overlaps between the signal ranges corresponding to individual peaks. A threshold in the valley between two overlapping peaks separates their main bodies but inevitably detects or rejects falsely some pixels with intermediate signals. The optimal threshold that minimises the expected numbers of false detections and rejections may not coincide with the lowest point in the valley between two overlapping peaks presented in figure 2:

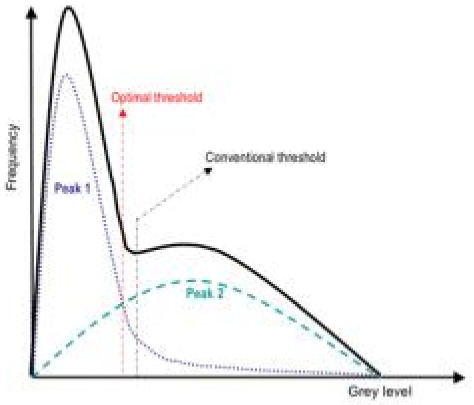

Fig. 2: The optimal threshold graph false detections and rejections.

Adaptive Thresholding :

Since the threshold separates the background from the object, the adaptive separation may take account of empirical probability distributions of object (e.g. dark) and background (bright) pixels. Such a threshold has to equalise two kinds of expected errors: of assigning a background pixel to the object and of assigning an object pixel to the background. More complex adaptive thresholding techniques use a spatially varying threshold to compensate for local spatial context effects (such a spatially varying threshold can be thought as a background normalisation) [19].

A simple iterative adaptation of the threshold is based on successive refinement of the estimated peak positions. It assumes that (i) each peak coincides with the mean grey level for all pixels that relate to that peak and (ii) the pixel probability decreases monotonically on the absolute difference between the pixel and peak values both for an object and background peak. The classification of the object and background pixels is done at each iteration j by using the threshold Tj found at previous iteration. Thus, at iteration j, each grey level f(x,y) is assigned first to the object or background class (region) if f(x,y) ≤ Tj or f(x,y) > Tj, respectively. Then, the new threshold, Tj+1 = 0.5(μj,ob + μj,bg) where μj,ob and μj,bg denote the mean grey level at iteration j for the found object and background pixels, respectively.

Contextual segmentation -Region growing :

Non-contextual thresholding groups pixels with no account of their relative locations in the image plane. Contextual segmentation can be more successful in separating individual objects because it accounts for closeness of pixels that belong to an individual object. Two basic approaches to contextual segmentation are based on signal discontinuity or similarity. Discontinuity-based techniques attempt to find complete boundaries enclosing relatively uniform regions assuming abrupt signal changes across each boundary. Similarity-based techniques attempt to directly create these uniform regions by grouping together connected pixels that satisfy certain similarity criteria. Both the approaches mirror each other, in the sense that a complete boundary splits one region into two [20].

Pixel connectivity :

Pixel connectivity is defined in terms of pixel neighbourhoods. A normal rectangular sampling pattern producing a finite arithmetic lattice {(x,y): x = 0, 1, ..., X−1; y = 0, 1, ..., Y−1} supporting digital images allows us to define two types of neighbourhood surrounding a pixel. A 4-neighbourhood {(x−1,y), (x,y+1), (x+1,y), (x,y−1)} contains only the pixels above, below, to the left and to the right of the central pixel (x,y). An 8-neighbourhood adds to the 4-neighbourhood four diagonal neighbours: {(x−1,y−1),(x−1,y), (x−1,y+1), (x,y+1), (x+1,y+1), (x+1,y), (x+1,y−1), (x,y−1)}.

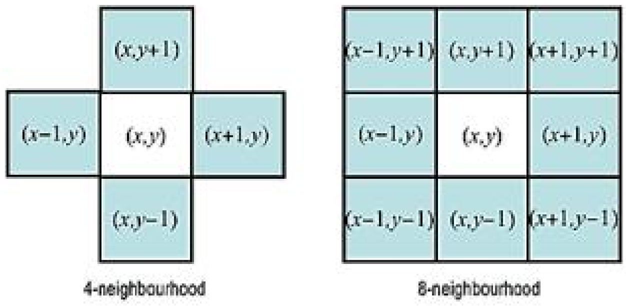

Fig. 3: four and eight connected path

A 4-connected path from a pixel p1 to another pixel pn is defined as the sequence of pixels {p1, p2, ..., pn} such that pi+1 is a 4-neighbour of pi for all i = 1, ..., n−1. The path is 8-connected if pi+1 is an 8-neighbour of pi. A set of pixels is a 4-connected region if there exists at least one 4-connected path between any pair of pixels from that set. The 8-connected region has at least one 8-connected path between any pair of pixels from that set [21-24].

Split-and-merge segmentation :

The top-down split-and-merge algorithm considers initially the entire image to be a single region and then iteratively splits each region into subregions or merges adjacent regions until all regions become uniform or until the desired number of regions have been established.

A common splitting strategy for a square image is to divide it recursively into smaller and smaller quadrants until, for any region R, the uniformity predicate P(R) is TRUE. The strategy builds a top-down quadtree: if P(image) is FALSE, the image is divided into four quadrants; if P(quadrant) is FALSE, the quadrant is divided into subquadrants; and so on:

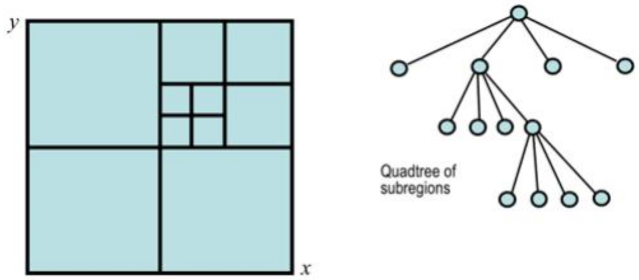

Fig. 4: common splitting strategy of square as quadtree

The splitting stage alternates with a merging stage, in which two adjacent regions Ri and Rj are combined into a new, larger region if the uniformity predicate for the union of these two regions, P(Ri ∪ Rj), is TRUE [25-27].

Clustering methods :

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The basic algorithm is Pick K cluster centers, either randomly or based on some heuristic method. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

Histogram-based methods:

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure.

A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This operation is repeated with smaller and smaller clusters until no more clusters are formed. One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image.

Histogram-based approaches can also be quickly adapted to apply to multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per-pixel basis where the resulting information is used to determine the most frequent color for the pixel location [28,29]. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in video tracking. Table 2 presents various segmentation methods.

Table 2 – Research that has been performed related to the segmentation of skin lesions in images.

Segmentation method	Technique
Edge-based	Edge detectors
Thresholding-based	Otsu's thresholding
	Fuzzy logic
	Renyi's entropy
	Adaptive thresholding
	Iterative thresholding
	Ensemble
	Statistics
Region-based	Region growing
	Statistical region merging
	Iterative stochastic region merging
AI-based	Neural networks
	Evolutionary computation
	Fuzzy logic
	k-means clustering
Active contour-based	Adaptive snake
	Gradient vector flow
	Level set
	Region-based active contour algorithm
	Active contour without edges
	Expectation-maximization level set
Other methods	Hill-climbing algorithm
	Dynamic programming

IV. RESEARCH CHALLENGES IN MELANOMA CANCER DETECTION

There are numerous research assortments in the programmed skin cancer diagnosis system that prerequisites to be addressed. First in image re-processing clatter removal in the prominent area that needs researcher’s attention. There are some algorithms for noise removal but their results are not promising. Regarding segmentation a lot of research work is required to develop the segmentation algorithms with superior accuracy in terms of the detection of the lesion edges, as well as to take into account other issues in the development of computational solutions, such as computational performance and automaticity level [30].

Selecting the optimal features for training the algorithms is another area that needs to be addressed. Many features are associated with the skin lesions but how to select the minimum numbers of features that provide the best results in terms of accuracy, complexity, computational time and performance is a challenging task. Mobiles phones have limited space and computational power therefore to design the classification algorithm for mobile based skin cancer diagnosis system that provides the real time results with higher accuracy is a big challenge that needs to be addressed [31]. The figure 5 address the different segmentation methods usage in the state of the art literature.

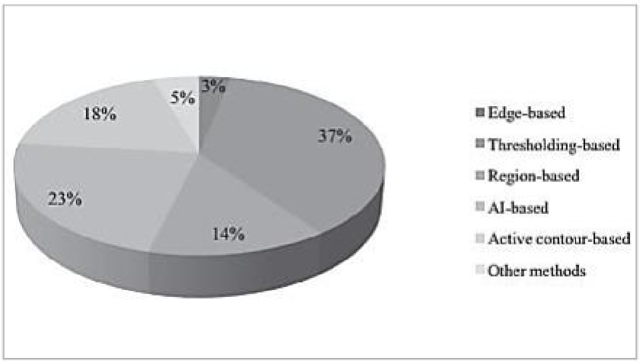

Fig. 5 : Distribution of the reviewed methods for the Segmentation of skin lesions according to the applied Principle.

V. CONCLUSIONS

Skin image region of interest segmentation is a significant step for the operative computational analysis of pigmented skin lesions in images. Skin lesion finding is a domain of increased attention due to both the prominence of prevention and to primary diagnosis of skin cancer. Although the image segmentation of skin lesions has been addressed in numerous research studies and successful applications, there is the potential to advance new methodologies and to enhance the performance of existing methods. Here, we have presented a case study / review about present methods that have been proposed to segment skin lesions.

From the summarized review, one may conclude that dermoscopy images should be more frequently used in the computational diagnosis of skin lesions, since these images present less artifacts and more comprehensive features, which may lead to more passable lesion segmentation and analysis. Nevertheless, techniques to remove or condense the artifacts are usually needed to gain robust segmentation results. The reviewed segmentation techniques were classified into: edge-, thresholding-, region-, AI- and active contour based and other categories. We have presented and discussed results obtained with some of these techniques applied to dermoscopy and macroscopic images of skin lesions. Active contour models can provide good results on images with colour variation and low contrast of the lesion boundaries.

Therefore, such prototypes are a good option for the segmentation of skin lesions. However, other methods with enhancements, or in combination with other techniques, may also provide good lesion detections.

In conclusion, the future trends regarding the image segmentation of skin lesions are to search for superior accuracy in terms of the detection of the lesion edges, as well as to take into account other issues in the development of computational solutions, such as computational performance, automaticity level, image noise smoothing and removal, and image enhancement.

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