International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

Skin Texture based Smart Detection of Skin infections by Image Segmentation Using Hybrid DWT and Watershed Transform

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Abstract: Extraction of features from the biomedical image using the texture and color space based image processing analysis algorithm is developed using hybrid of DWT, entropy filtering and watershed transform is discussed in this article. To extract the textures we have used entropy features using function on the Matlab algorithm where it corresponds to the input image parameter with the use of spatial based parameters. The texture analysis based skin texture extraction algorithm consists of steps related to decomposing the input image into a set of binary images from which the color space dimensions of the resulting regions can be computed in order to describe segmented texture patterns.

Keywords: Segmentation, skin infections, DWT, Watershed transform and Image morphology.

1. Introduction:

Skin cancer is one of the most increasing cancers in the world. For instance, it was reported in [1] that one in six Americans develops skin cancer at some point. Skin cancer accounts for one third of all cancers in the United States, and in particular malignant melanoma accounts for 75% of all deaths associated with skin cancer [1]. Early detection greatly improves the prognosis of patients with malignant melanoma, since it can be cured with a simple excision. In order to diagnose skin lesions, physicians assess the lesion based on different rules. For melanocytic lesions, one of the most famous is the ABCD rule (Asymmetry, Border, Colour, Diameter) [2]. An expert dermatologist, however, after learning from huge amount of lesions, seems to develop the ability to diagnose skin lesions using pattern analysis. Pattern analysis of skin lesions is receiving attention in literature. For instance, Serrano and Acha [3] recently proposed a method based on Markov random fields for detection of patterns in dermoscopic images. The best classification rate in the task of discriminating between reticular, globular, cobblestone, homogeneous, and parallel pattern was 86%. For each specific pattern considered, 40_40 image samples were used to train the classifier. Although these patterns are expected to be diagnostically useful, the performance in terms of final diagnosis remains to be investigated. Contrary to traditional algorithms designed to mimic rules like the ABCD, we propose a method that automatically discriminates relevant features indicative of malignancy or benignancy in melanocytic skin lesions, provided that a good database of the kind of lesions of interest is available for learning.

In 1992, Stoecker and Moss summarized in their editorial the potential benefits of applying digital imaging to dermatology [5]. These benefits were viewed according to the technology available at the time, including of course the capabilities of computer vision techniques, and the results of the earlier research in the area (e.g. [6]). Among others, these included objective non-invasive documentation of skin lesions, systems for their diagnostic assistance by malignancy scoring, identifying changes, and telediagnosis. This was the first time a journal had dedicated an entire special issue to methods for computerized analysis of images in dermatology specifically applied to skin cancer. Now, almost two decades later, the 2011 publication of the second special issue—Advances in skin cancer image analysis [4]—allows us to clearly see the changes that have taken place in this field. More importantly, we are able to see how close we are to making certain benefits real rather than potential, and which ones have turned out to be even more beneficial than initially predicted.

As sometimes happens with disciplines related to two essentially different fields of study like dermatology and computer vision, there can be certain ambiguities in overlapping terminology. These ambiguities may easily mislead readers not familiar with one of the fields, thus forcing them to draw false conclusions about the subject. Therefore, in order to facilitate the introduction of computer vision researchers into the field of dermatological image analysis, this paper provides detailed guidance in the relevant medical material.

Skin is the largest organ in the human body and consists of two principal layers2: the epidermis and the dermis (see Fig. 1). The epidermis is a stratified squamous epithelium, a layered scalelike tissue, which serves as protection against external aggressions (injuries, infections, ultraviolet radiation and water loss).

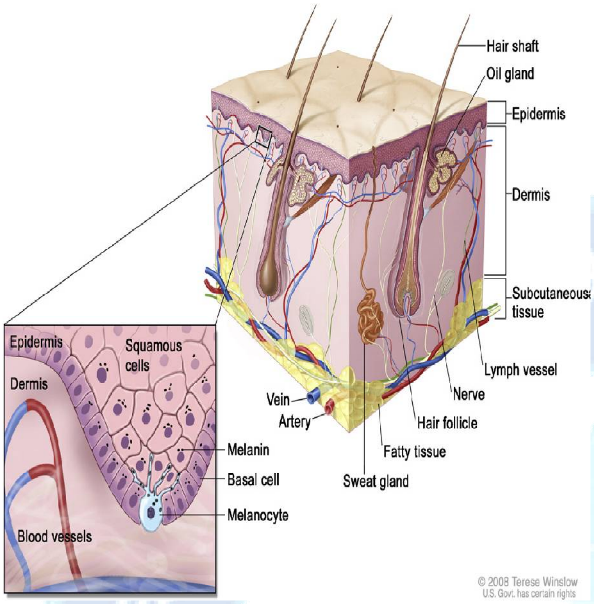


Fig. 1. Anatomy of the skin, showing the epidermis, the dermis, and subcutaneous (hypodermic) tissue.

2. Image Segmentation:

The use of colour and texture information collectively has strong links with the human perception and in many practical scenarios the colour-alone or texture-alone image information is not sufficiently robust to accurately describe the image content. An example is provided by the segmentation of natural images that exhibit both colour and texture characteristics. This intuitive psychophysical observation prompted the computer vision researchers to investigate a large spectrum of mathematical models with the aim of sampling the local and global properties of these two fundamental image descriptors. Nonetheless, the robust integration of colour and texture attributes is far from a trivial objective and this is motivated, in part, by the difficulty in extracting precise colour and texture models that can locally adapt to the variations in the image content. In particular the segmentation of natural images proved to be a challenging task, since these images exhibit significant inhomogeneities in colour and texture and in addition they are often characterised by a high degree of complexity, randomness and irregularity. Moreover, the strength of texture and colour attributes can vary considerably from image to image and complications added by the uneven illumination, image noise, perspective and scale distortions make the process of identifying the homogenous image regions extremely difficult. All these challenges attracted substantial interest from the vision researchers, as the robust integration of the colour and texture descriptors in the segmentation process has major implications in the development of higher-level image analysis tasks such as object recognition, scene understanding, image indexing and retrieval, etc.

Over the past three decades, the field of image segmentation based on the integration of colour and texture descriptors has developed extensively, peaking with an abundance of algorithms published between the years 2007 and 2009. It is useful to note that in the period covered between 1984 and 2009 more than 1000 papers have been published in the literature and this figure acknowledges the fact that colour–texture analysis has positioned itself as one of the most researched areas in the field of image processing and computer vision. The statistics that evaluate the number of algorithms published on the topic of colour–texture analysis in the last three years (2007–2009) clearly indicate that this field of research has reached maturity and, as a result, distinct patterns or categories of approaches that sample either the nature of the feature extraction process or the methodologies employed for feature integration can be identified. The aim of this paper is to analyse from a theoretical perspective the main directions of research in the field of colour–texture analysis and to review the concepts and strategies that have been investigated in the process of colour–texture integration with a view of attaining robust image segmentation. Although several surveys have addressed the evaluation of colour-alone [1–3] or texture-alone [4–9] segmentation algorithms, we are not aware of any work in the literature that was concerned with the systematic analysis of the concepts and methodologies that were employed in the development of colour–texture image segmentation algorithms. We would like to emphasise that in this review we are particularly concerned with the analysis and categorisation of the published works with respect to the integration of colour and texture information in the segmentation process, which, in our opinion, is the only logical approach that can lead to a meaningful insight into this important field of research. There are mainly two reasons that justify the adopted approach. Firstly, such analysis facilitates a precise categorisation of the published algorithm based on the principles behind data fusion (feature integration) process, which is the central issue in the development of colour–texture segmentation schemes, and secondly such line of investigation will further allow the identification of generic colour–texture integration patterns that are decoupled from the application context that is the prevalent characteristic of the colour and texture feature extraction techniques. Thus, the foremost objectives of this paper are: (a) to categorise the main trends in colour–texture integration, (b) to sample the application context of the proposed implementations (whenever such discussion is appropriate), (c) to discuss the evaluation metrics that are currently used to assess the performance of the segmentation techniques, (d) to review the publicly available data collections (image databases) and (e) to analyse the performance of well-established state of the art implementations. It is useful to note that this review is primarily concerned with the analysis of algorithms that have been designed for the segmentation of still digital images and we will indicate when the evaluated approaches have been applied to the segmentation of video data. To provide a comprehensive insight into the work in the field of colour–texture segmentation, we analysed a substantial number of papers published in journals and conference proceedings. To broaden the scope of this paper, we will not restrict ourselves only to the technical assessment of the investigated

algorithms, but we will also try to provide an ample discussion where the ideas that emerged in the field of colour–texture integration over the past three decades are systematically categorised and we will examine the practical context of the investigated methods whenever such discussion is possible. Also, we will place an important emphasis on the quantitative evaluation of the state of the art implementations in the field of colour–texture analysis. In this regard, we will present the numerical results achieved by the analysed state of the art methods and we will indicate the conditions and the type of data used in the evaluation process.
Medical images play vital role in assisting health care providers to access patients for diagnosis and treatment. Studying medical images depends mainly on the visual interpretation of the radiologists. However, this consumes time and usually subjective, depending on the experience of the radiologist. Consequently the use of computer-aided systems becomes very necessary to overcome these limitations. Artificial Intelligence methods such as digital image processing when combined with others like machine learning, fuzzy logic and pattern recognition are so valuable in Image techniques can be grouped under a general framework; Image Engineering (IE). This is comprised of three layers: image processing (lower layer), image analysis (middle layer), and image understanding (high layer), as shown in Fig 2. Image segmentation is shown to be the first step and also one of the most critical tasks of image analysis. Its objective is that of extracting information (represented by data) from an image via image segmentation, object representation, and feature measurement, as shown in Fig 2. Result of segmentation; obviously have considerable influence over the accuracy of feature measurement [2]. The computerization of medical image segmentation plays an important role in medical imaging applications. It has found wide application in different areas such as diagnosis, localization of pathology, study of anatomical structure, treatment planning, and computer-integrated surgery. However, the variability and the complexity of the anatomical structures in the human body have resulted in medical image segmentation remaining a hard problem [3].

Based on different technologies, image segmentation approaches are currently divided into following categories, based on two properties of image.

3. Methodology:

The objective of work is to perform image segmentation by partitioning them into disjoint clusters with equivalent performance of human perception of the region of interest. It will be an unsupervised segmentation of organs scanned images which accomplish the requirement of making prior assumptions about the ROI. We will apply a two-stage method for such images segmentation will be performed that can process both textured and non-textured. First stage calculates textured features from the bands coefficients of the dual-tree wavelet transform of image. Thereafter median filtering will be applied to minimize the ambiguities of texture regions at the boundaries of the image objects.

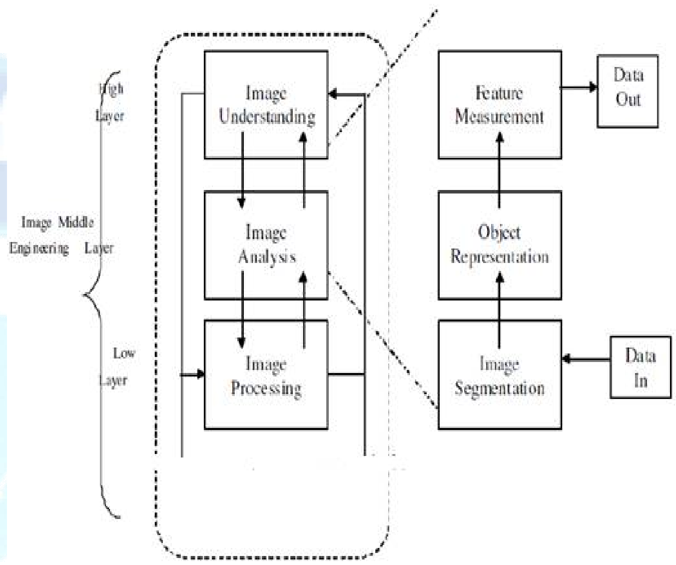


Fig 2: Image engineering and image segmentation [2].

The calculated texture feature will be used to find the space based gradient function and then watershed transform will be applied to obtain the initial segmentation.
The second stage the segmented regions obtained by watershed transform are grouped to meaningful region of similar features by using spectral clustering technique by using the weighted mean based cost function for region partitioning.

Algorithm:

1. **Image acquisition:** Read the biomedical image (I) and perform image resizing and select region of interest that is to be cropped.
2. **1 level Image DWT:** Perform the first level 2d DWT on the image and obtain the approximation component (A) of the transformed data.
   [A DH DV DD]= DWT (I)
3. **2 level Image DWT:** Perform the second level 2d DWT on the image and obtain the next approximation component (A1) of the transformed data.
   [A1 DH1 DV1 DD1]= DWT(A)
4. **Approximated Image Reconstruction by 2level IDWT:** Perform inverse DWT and reconstruct the image by considering only approx component and suppressing the DH, DV and DD detailed component.
5. **Entropy filtering:** Apply entropy filtering to reconstruct approximated image.
6. **Remove small objects:** Remove the unwanted openings having size less than 100 pixels.

International Journal of Research and Development in Applied Science and Engineering (IJRDASE)
ISSN: 2454-6844

7. **Morphological Processing:** Apply image closing and filling operations to eliminate noise in the filtered image.
8. **Texture Masking:** Mask the texture 1 and texture 2 to develop texture based segmented image.
9. **Edge Detection:** Apply sobel filtering for highlighting the edge boundaries and then determine the gradient magnitude to get image having one at boundaries otherwise zero for inner regions.
10. **Edge Erosion:** Apply erosion of object less than disk size 4 pixel and perform reconstruction.
11. **Edge dilation:** Apply dilation of object less than disk size 4 pixel and perform reconstruction.
12. **Thresholding:** Apply the threshold on edge objects to selects the segmented boundaries to high intensity.
13. **Watershed Transform:** Apply watershed transform on the image obtained after segmentation.
14. **Superimposing of segmented image:** Superimpose texture based segments image over the watershed transform applied segmented image by alpha blending.

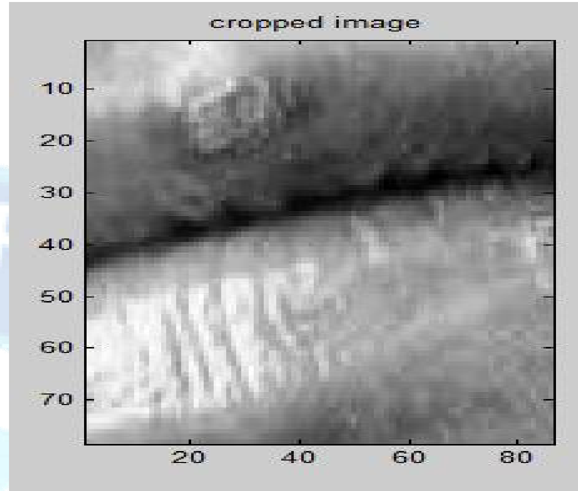
4. Result and Discussion:

The images are taken from link. The link consist of 44 skin disorders details and the image. We have considered 16 images http://www.healthline.com/health/skin-disorders.The fig 3 is for Canker sore infection image having name **'194x105_Canker_Sore.jpg'** . A canker sore, or aphthous ulcer, is an open and painful mouth ulcer or sore. It's also the most common type of mouth ulcer. Some people notice them inside their lips or cheeks. They're usually white or yellow and surrounded by red, inflamed soft tissue. Canker sore symptoms include:

- a small white or yellow oval-shaped ulcer in your mouth
- a painful red area in your mouth

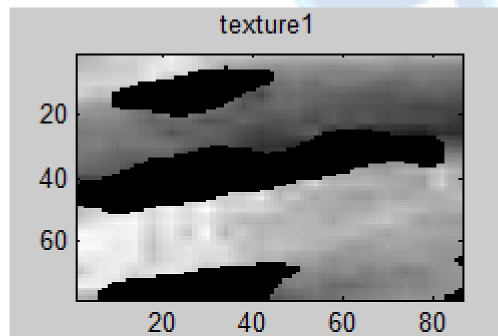
Fig 3 g shows the segmented result. It can be observed that the infected portion is segmented properly and encircled by the whit boundary.

(i)

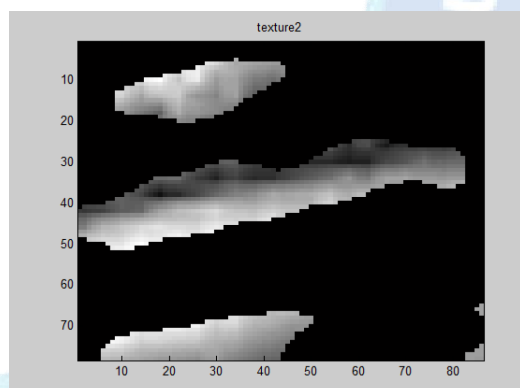


(ii)

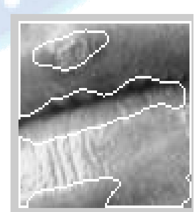
3 (a): Original (i) and Cropped Image(ii)



3 (b): Texture 1



3 (c): Texture 2



3 (d): Texture based Segment Image

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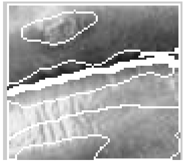
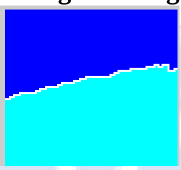
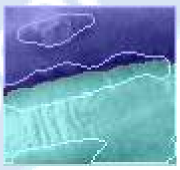


3 (e): Marked and Object Boundaries Superimposed on Original Image



3 (f): Colored Watershed label Matrix (LRGB)



3 (g): LRGB Superimposed Transparently on Original Image

Fig 3: Image Segmentation result for '194x105_Canker_Sore.jpg' image.

The figure 4 is for other skin infection image having different cultivation symtoms on different dody area. Figure shows that the segmentations are perfectly encircling the infected portion and also shows the desired infected portion in boundaries and in different colour.

Fig 4(a): Cellulitis infection Original image

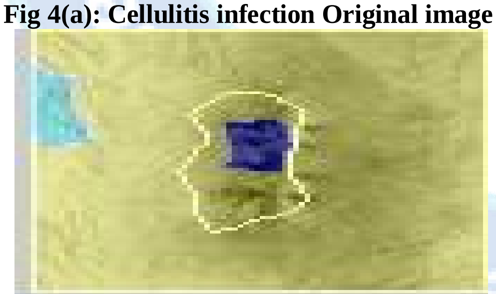


Fig 4(b): Cellulitis infection Segmented image

Fig 5(a):Cold sore infection Original image

Fig 5(b):Cold sore infection Segmented image

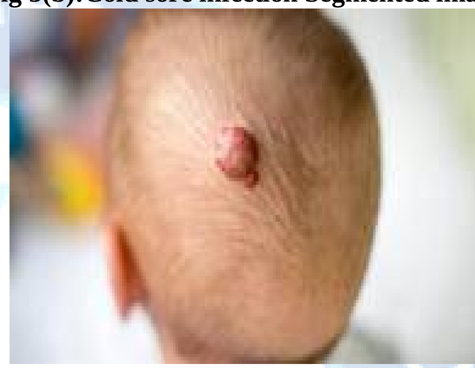


Fig 6(a):Hemangioma of Skin infection Original image.

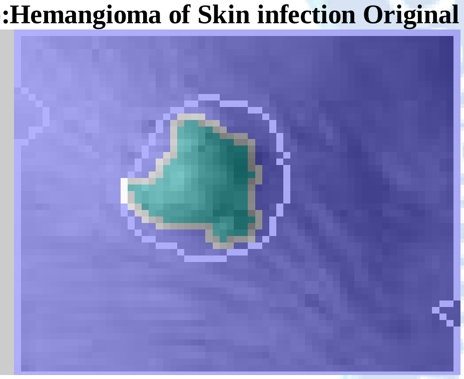


Fig 6(b):Hemangioma of Skin infection Segmented image.

Fig 7(a): Lichen_Planus infection Original image.

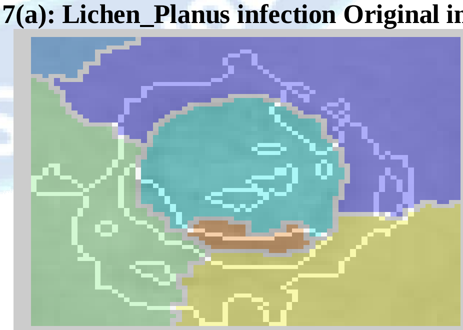


Fig 7(b): Lichen_Planus infection Segmented image.

5. Conclusion:

Texture and coarseness of organs are visually different. On applying image processing in the segmentation analysis it is found helpful to quantitatively evaluate differences texture features when applied on wavelet approximated component.

We have reviewed several journal articles to study various image segmentation techniques. Most of the techniques face similar problems like inadaptability to different modalities, vast amount of data to segment and noise involved. The texture is the appearance of the smooth surface. To the features of this texture, many factors are occurring, for instance diet and hydration, amount of collagen and hormones, and, of course skin care. A gradual decline in segmentation quality moreover occurs due to superimposing of high level details. As details increases thinner image patterns are developed and more easily damage the segmentation quality with the appearance of lines and irregular thin objects. The deterioration is also accompanied by a darkening of the background or boundary colour for an over absorption of the natural colouring pigment, melanin, by the top most cell layer of body organs. The texture also depends on its body location. In the case of image processing, we have considered the fact that texture appearance is changing with image recording parameters, i.e. camera, illumination and direction of view, a problem common to any real surface.

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