International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 5, No. 3, August 2016

Research Paper

DESIGN AND IMPLEMENTATION OF FPGA-BASED SKIN CANCER DETECTION USING SEGMENTATION RULES

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Automated detection of cancerous tissue in histopathological images is a big challenge. This work proposed a new pattern recognition method for histopathological image analysis for identification of cancerous tissues. It comprised of feature extraction using a combination of wavelet and intensity based statistical features and autoregressive parameters. Moreover, differential evolution based feature selection is used for dimensionality reduction and an efficient self-advised version of support vector machine is used for evaluation of selected features and for the classification of images. The proposed system is trained and tested using a dataset of 150 histopathological images and showed promising comparative results with an average diagnostic accuracy of 89.1.

Keywords: FPGA, Histopathological image, Asymmetry Index

INTRODUCTION

Skin cancer is the most common form of human cancer if melanoma, basal and squamous cell skin cancers are included. The annual rates of all forms of skin cancer are increasing each year, representing a growing public concern. Based on the Cancer Trends Progress Report by National Institute of Health of United States (NIH), it is estimated that nearly half of all Americans who live to age 65 will develop skin cancer at least once. Malignant melanoma, the most deadly form of skin cancer, is one of the most rapidly increasing cancers in the world. Melanoma is now the 7th most frequent cancer in Canada affecting 5,300 people in 2010 and causing 920 deaths and the 5th most common malignancy in the United States. 10710 deaths out of 21,700 incidences are estimated numbers in the United States during 2012. Metastatic melanoma is very difficult to treat, so the best treatment is still early diagnosis and prompt surgical excision of the primary cancer so that it can be completely excised while it is

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still localized. Therefore, advances in computer-aided diagnostic methods can aid self-examining approaches based on digital images, and may significantly reduce the mortality. This project investigates and reviews important aspects of automated analysis of skin lesions using digital dermoscopy images and proposes a novel approach for automated detection of the two important dermoscopy structures: pigment network and streaks.

PROBLEM DEFINITION AND MOTIVATION

As mentioned in the previous section, melanoma is now the 7th most frequent cancer in Canada. Over the past 31 years, more people have had skin cancer than all other cancers combined. In addition, unlike many cancers, melanoma is clearly visible on the skin and up to 70% of all melanomas are first identified by the patients themselves (53%) or close family members (17%).

Therefore, advances in computer-aided diagnostic methods can aid self-examination approaches and reduce the mortality significantly. Dermoscopy, a non-invasive skin imaging techniques, has become a principal tool in the diagnosis of melanoma and other pigmented skin lesions. It involves optical magnification of the region-of-interest, which makes subsurface structures more visible than conventional macroscopic images. However, it has also been demonstrated that dermoscopy may actually lower the diagnostic accuracy in the hands of inexperienced dermatologists. Therefore, computerized image understanding tools are needed to minimize the diagnostic errors. These errors are generally caused by the complexity of the subsurface structures and the subjectivity of visual interpretations.

In almost all of the clinical dermoscopy methods, dermatologists look for the presence of specific visual features for making a diagnosis. Then, these features are analyzed for irregularities and malignancy.

To simulate an expert's diagnostic approach, an automated analysis of dermoscopy images re-quires several steps. Delineation of the region of interest, which has been widely addressed in the literature, is always the first essential step in a computerized analysis of skin lesion images. The border characteristics provide essential 2 information for an accurate diagnosis. For instance, asymmetry, border irregularity, and abrupt border cutoff are some of the critical features calculated based on the lesion border [66]. Furthermore, the extraction of other critical clinical indicators and dermoscopy structures such as atypical pigment networks, globules, and blue-white areas depend on the border detection. The next essential step is the detection and analysis of the key diagnostic features of the dermoscopic structures. Automatic detection and analysis of the key diagnostic features of the some of these dermoscopic structures has been recently addressed in the literature and will be reviewed in the following chapters.

The problem addressed in this project is how to analyze a given digital dermoscopic image for detecting pigment networks and streaks, and quantifying the irregularity of these structures, for use in diagnosing cancerous lesions especially melanoma. Images discussed in this project are a combination of images by oil immersion (non-polarised) dermoscopy and cross-polarized imaging.

Figure 1: A Typical Medical Imaging System

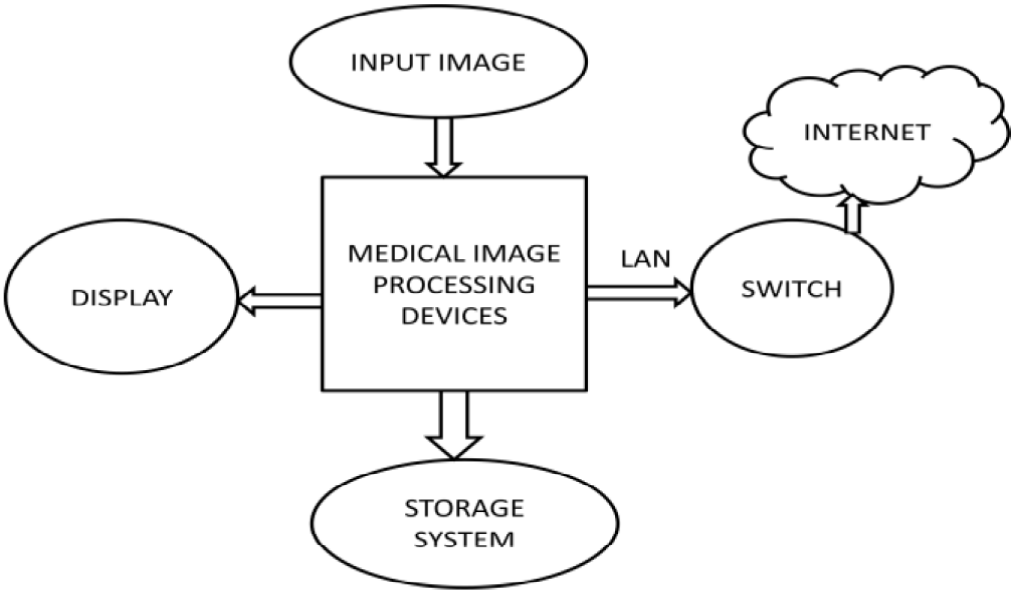
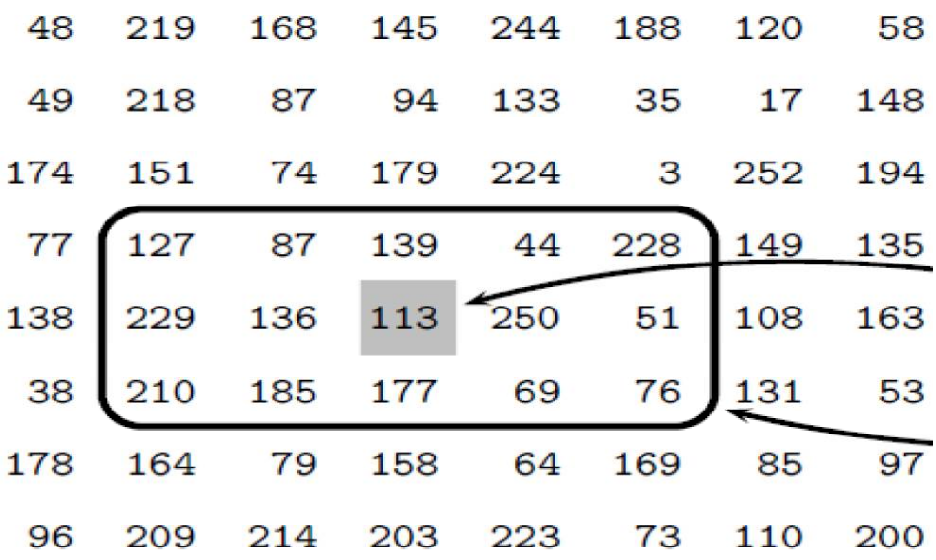


Figure 2: Skin Lesion Segmentation



The Random Walker (RW) algorithm is a general purpose interactive multi-label segmentation technique where a user labels the image with 'seed points' which denote the ground truth label for that pixel. Then, for an arbitrary pixel, the probability of a random walker reaching a seed of a specific label (before reaching seeds of any other label) is computed. However, the RW

algorithm is sensitive to the exact placement of seeds and to the number of seeds placed. While the RW algorithm is fast, intuitive and robust, it has been determined that a large number of seed points (up to 50% of the image) is required to reproduce a segmentation with only minor differences.

We have adopted the RW method described above into a novel framework, to automatically segment skin lesions from dermoscopic images.

METHOD

In this chapter we present an approach to leverage the advantages of RW for automatic skin lesion segmentation. We initialize the RW algorithm automatically with seed points generated by 'learning' (by means of a training set) the difference between the properties of 'skin lesion pixels' and 'healthy skin pixels'.

Skin Lesion Segmentation Using Automated Random Walker

Supervised Probabilistic Segmentation

We begin with a set of 120 expertly segmented dermoscopic images taken from an atlas (Masood, 2014)[100]. Each pixel is assigned either the label 'inside' (l1) or 'outside' (l2) based on the ground truth segmentation. In this stage we aim to learn the difference between these two groups. Images are converted to L*a*b* space, and each channel is filtered with a set of Gaussian and Laplacian of Gaussian filters. Let m denote the number of filters employed. Pixels are then represented as a1 × 3m vector since each filter is applied to each of the 3 image channels. Linear Discriminant Analysis (LDA) [35] is then used to determine the linear combination of filters tha t best discriminate `inside' and `outside' pixels. LDA is similar to Principal Component Analysis (PCA), but where PCA is an unsupervised technique that reduces dimensionality while maintaining variance, LDA is a supervised technique that reduces dimensionality while maintaining class separability. This is achieved through an eigenvalue decomposition of an 3 m × 3 m scatter matrix, which represents the separability of the classes with respect to each filter. Since this is a 2-class problem, we consider only the principle eigenvector. This eigenvector results in a linear combination of the filter sets for each image channel. Since the filterset employed is a series of low-pass (Gaussian) and high-pass (Laplacian of Gaussian) filters, the resulting `eigenfilters' can be interpreted as either a high, low, or multiple-band-pass filters. This filter bank includes five Gaussian and five Laplacian of Gaussian filters applied to the three channels of the L*a*b* space, that results 30 filter r responses in total. We are therefore not only learning the color difference between these two groups of pixels, but also the difference in the spatial variation of colors.

Next, the response of the pixel groups ('inside' and 'outside') along this eigenvector are modeled.

We create probability maps for unseen images by filtering the image with the resultin g eigenfilters from LDA, and for each pixel p, assigning it a normalized probability that the pixel is inside the lesion. The creation of a probability map is illustrated in Figure 3.

Learning the difference between pixels inside and outside the segmentation. 3a)-3d): Some filters from the filter set applied to each channel of each image. The filter set consists of Gaussian filters (Figures 3a and 3b) and Laplacian of Gaussian filters (Figures 3c and 3d) and the 'eigenfilters' a s a result of LDA for the L*, a* and b* channels respectively (Figures 3e, 3f and 3g)

Figure 3: Creation of a Supervised Probabilistic Segmentation

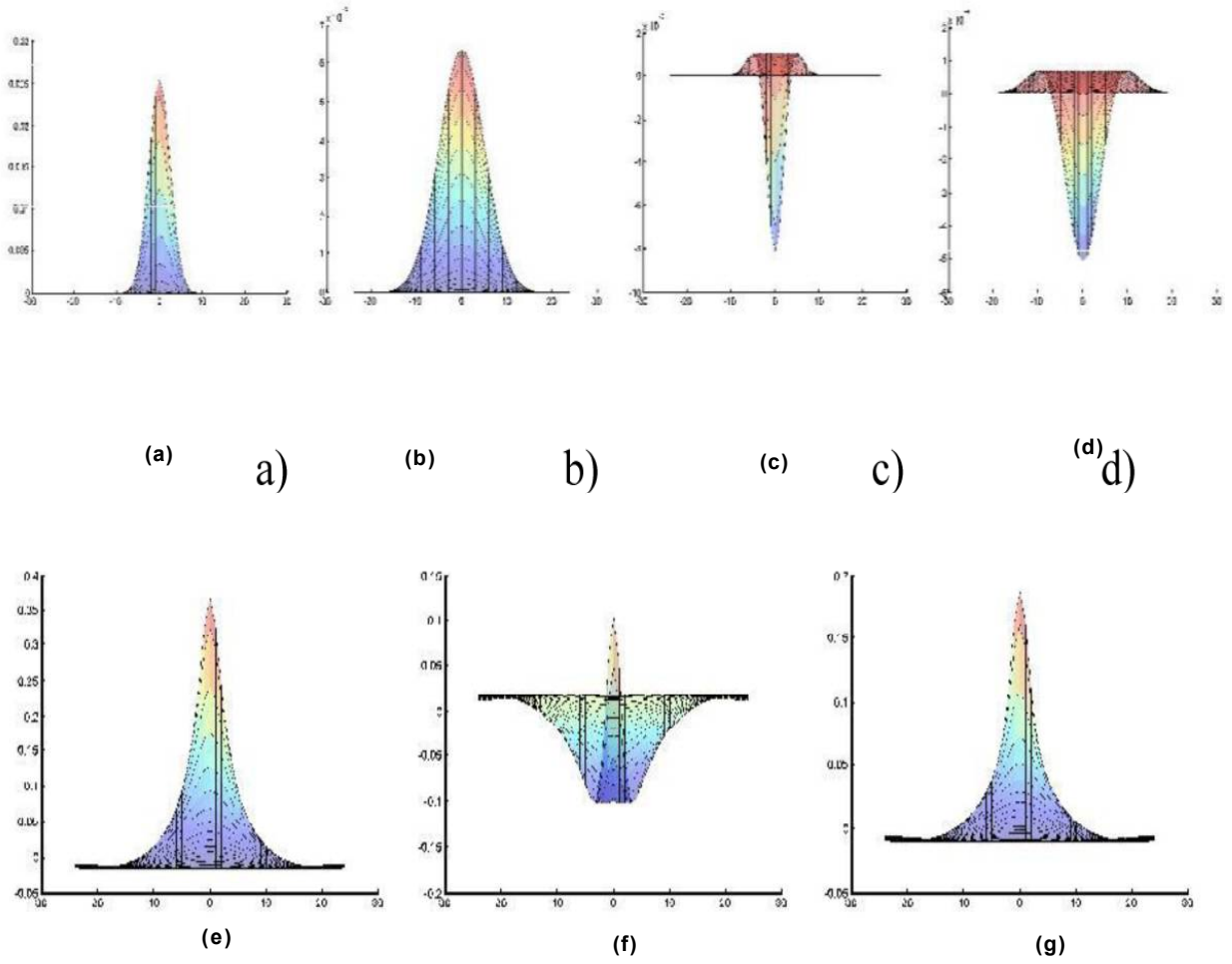


Figure 3 shows that the creation of a supervised probabilistic segmentation, a) the original dermoscopic image, b) the image's response to the 'eigen filter' from Figure 3(c) the resulting probability map by applying equation 2. Note the high response to the photo damaged skin to the right of the lesion. This is due to the fact that this pattern (known as a pigment network) usually occurs within lesions.

PREVIOUS WORK

Computer-aided diagnosis of dermoscopy images has shown a great promise in developing a quantitative and objective way of classifying skin lesions. A non-invasive computer-aided diagnostic system typically consists of several components: image acquisition, image processing, and a classifier with a knowledge database. When a melanocytic lesion is captured in viv o as a digital image using a dermoscope, the characteristics of the lesion can be extracted from the digital image by image processing techniques. Then a border detection should be applied to segment the lesion from normal skin and the lesion area should be investigated to find dermoscopic structures and irregularities. Feeding the features

to a classifier which is connected to a medical knowledge database can gene rate a computerized diagnosis, suggesting whether the lesion is benign or malignant.

In this chapter, the previous work on the main stages of a computer-aided diagnosis system are discussed. First, we review the preprocessing phase that includes the lesion segmentation task, and then consider previous work on the automated detection of pigment networks and streaks, which are the important dermoscopic structures.

FEATURE EXTRACTION

In order to diagnose skin lesion automatically we will follow feature extraction process. A process is based on the rule, i.e., ABCD-rule of dermatoscopy. ABCD stands for asymmetry, color, variation, border structure and dermatoscopical structure which is also called diameter of the lesion. This process defines the basis for a diagnosis by a dermatologist

Asymmetry

We can easily understand the aspect of shape with the help of symmetry which plays an important role in pattern analysis. In case of symmetric pattern, we need one half of the pattern along the axis of symmetry. If in a case a pattern part is missing or noisy then with the help of symmetry we can complete the pattern or rid the pattern of noisy. The degree of symmetry is determined using two values of asymmetry feature, i.e., Asymmetry Index (AI) and Lengthening Index. Asymmetry Index is calculated using equation:

$$AI = \Delta A/A*100$$

where, A= Area of the total Image. = Area difference between total image and lesion area.

Border Irregularity

To determine border irregularity, we will follow many different measures like: compactness index, fractal index, edge abruptness, pigment transition.

Color Variation

Melanoma is characterized into six different colours named as white, red, light brown, dark brown blue-grey and black. The variations in colour represent the early sign of Melanoma. As melanoma cells grows in grower pigment, thus they are colourful around brown, or black which depends on the production of the melanin pigment at various depths in the skin. The color descriptors are mainly statistical parameters which are calculated from different color channels, such as average value and standard deviation of the RGB or HSV color channel. The variation in color of the RGB image has been calculated with the help of HSV channel.

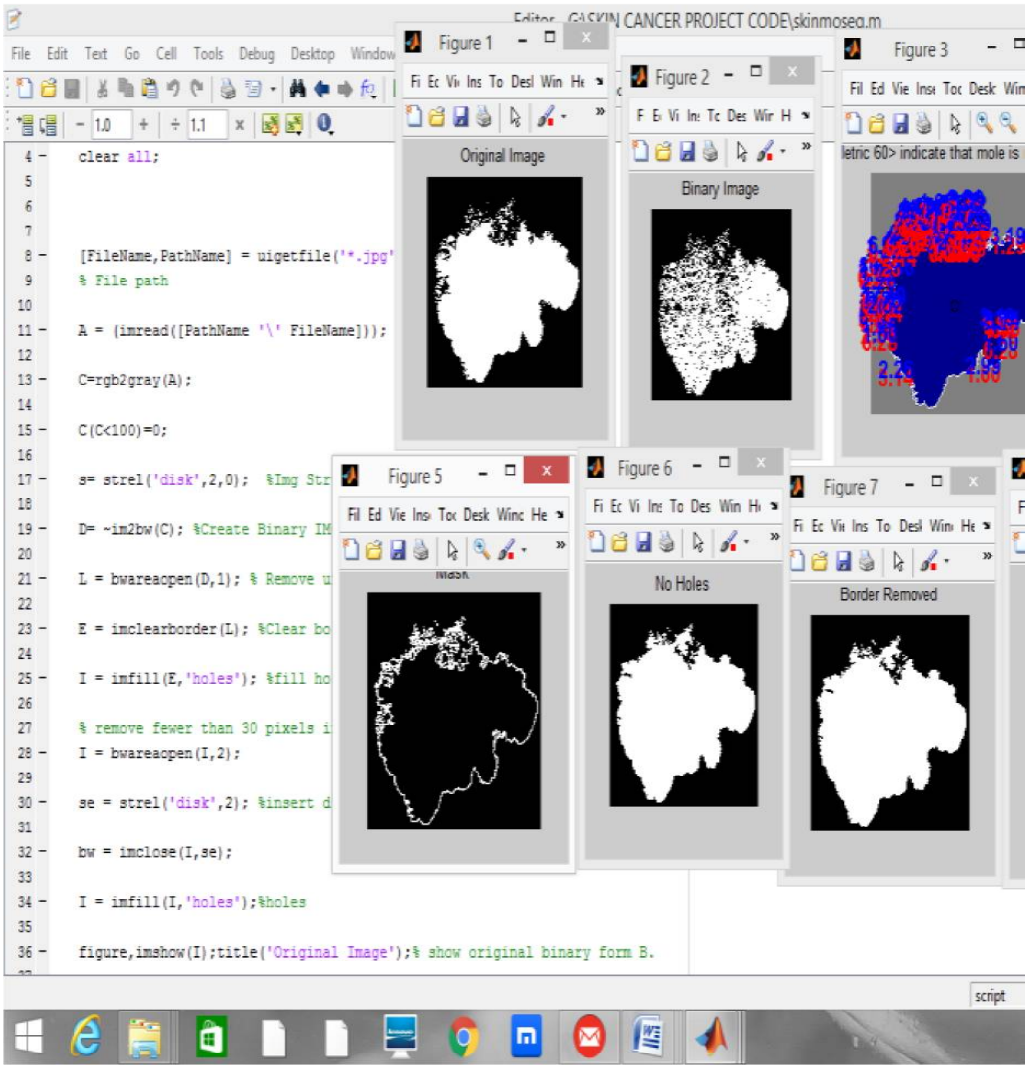
Diameter

The tendency of Melanoma growth is much larger than common moles, and having diameter of 6 mm. As the shapes of Melanoma changes thus we need to find the diameter from all the edge pixels to the pixel edge via midpoint and averaged.

CONCLUSION

The different methods have been discussed to find the cancer cells in the skin lesions. The different methods implemented are image acquisition, segmentation, preprocessing, feature extraction and detection methods. Here we use different image feature extraction through image processing methods and they are border, color, entropy, compactness, radial variance of the mask, coarseness. Based on these features, the risk probability factor of the lesion is shown with the help of computer aided diagnosis system.

Figure 4: Simulation Report



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