Biomedical Signal Processing and Control 44 (2018) 25–37

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A methodological approach to classify typical and atypical pigment network patterns for melanoma diagnosis

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ARTICLE INFO

Article history:
Received 26 November 2017
Received in revised form 12 March 2018
Accepted 30 March 2018

Keywords:
Atypical
Dermoscopy
Gabor
Polynomial curve fitting
Pigment network
Typical

ABSTRACT

The pigment network is considered as one of the most histopathologically relevant indicator of melanoma. The objective of this empirical study is to design a novel automatic system for detection of pigment network and provide a differentiation between typical and atypical network patterns. The algorithm design consists a set of sequential stages. Pigment network masks are detected using a bank of 2D Gabor filters, and a set of pigment network features are extracted to determine the role of pigment network in the diagnosis of the lesion. In the second stage, a machine learning process is carried out using the rules generated from the pigment network masks to identify the typical and atypical pigment network patterns. The proposed methodology was tested on the PH^2 dataset of 200 images, obtaining an average sensitivity of 96%, specificity of 100% and accuracy of 96.7% for lesion diagnosis, and an average sensitivity, specificity and accuracy of 84.6%, 88.7% and 86.7% respectively, for pigment network classification. The proposed system stands out amongst the few state of art literatures reported in the context of dermoscopic image analysis in terms of performance and methodologies adopted, thus proving the reliability of the proposed study.

1. Introduction

1.1. Motivation

Melanoma is considered as one of the most deadliest form of skin cancer associated with increased morbidity and medical costs as high as $3.3 billion [1]. Although, melanoma is detectable by simple observations, as it is confined to the skin, it is further liable to metastasize and spread to the lymph nodes. The primitive diagnosis mainly relies on the precise assessment by the dermatologist with the aid of dermoscope [2]. Melanoma prognosis is still subjective in spite of the well-established medical methods due to lack of experience, and variation in visual perception. Among the various dermoscopic structures, such as dots, globules, streaks, and blue-white veil, the pigment network holds clinical significance for identifying malignant lesions. Manual segmentation is time-consuming and prone to inter and intra observer variabilities. Thus, dermatologist use rough measures for evaluation.

For these reasons, semi-automatic and automatic accurate methods are required [3–5]. However, the segmentation of pigment network is an arduous and daunting task, since great variation exists in the shape, location and pigmentation of these structures. Additionally, the presence of hair in the dermoscopic images, relatively lower contrast between the background and the lines, artifacts such as air bubbles, ruler markings etc., create spurious ambiguities in the pigment network detection process.

1.2. Pathological significance of pigment network in melanoma diagnosis

The pigment network indicates the sign of growth of melanocytic lesions, since growing nevi distort the anatomy of the human skin thereby causing uneven variations. The network appears as a grid of thin brown lines over a light brown diffused background. Histopathologically, it corresponds to melanin pigment in the keratinocytes located along the basal layer at the dermo-epidermal junction. The pigment network is considered as the hallmark of melanocytic lesion. The pattern may be subtle in nature or present in a small area. Benign pigmented lesions such as lentigo or junctional nevus indicate signs of uniform network patterns. These lines are uniformly spaced indicating gradual growth rate of benign nevi. Such a pigmented network pattern is termed

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https://doi.org/10.1016/j.bspc.2018.03.017
1746-8094/

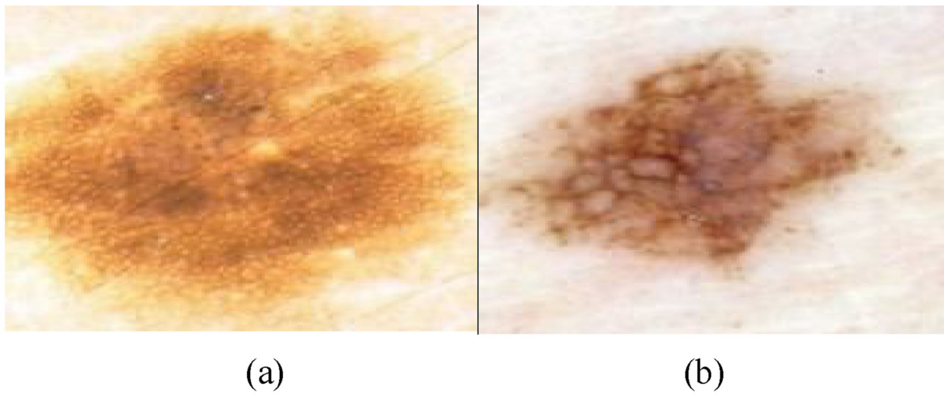

Fig. 1. Illustration of Pigment Network (a) Typical (b) Atypical [30].

as typical, as illustrated in Fig. 1(a). The network is homogenous in nature, which thins out at the periphery. In case of malignant lesions, melanocytes vary in size and degree of pigmentation. The malignant melanocytes migrate through the epidermis in all directions with varying rates, thus producing bizarre patterns, such patterns are termed as atypical [6], as illustrated in Fig. 1(b).

The accurate detection of pigment network and identification of the patterns is important not only for distinguishing benign and malignant lesions, but also for checking the prognosis of the lesions.

1.3. Related work

The detection and exclusion of dermoscopic hair forms a major step in the development of CAD system for melanoma diagnosis. The dermoscopic hair should be masked and removed, in order to increase the accuracy of diagnosis. Several approaches have been reported in literature for hair detection and exclusion [7–10]. However, most of these techniques are suitable for light hair. The proposed hair detection technique is computationally simple and efficiently detects light and dark hair. In order to develop a reliable clinically acceptable CAD system for melanoma diagnosis, it is necessary to incorporate the pigment network detection algorithm. In the seven-point checklist criteria, a score of 2 is assigned for the presence of pigment network. The presence of pigment network is considered to be one of the significant indicators of malignancy of melanocytic lesions, since it corresponds to the localization of melanin in the lower epidermis. In this regard, several works have been investigated and reported in literature [11–21]. The system proposed by Fischer et al. [11] is based on histogram equalization and morphological operations to enhance the pigment network patterns. Grayscale shape extraction based on the principles of differential geometry were utilized by Fleming et al. [12], wherein candidate line points with high principle curvature are linked using a hysteresis operation. For each line point, associated line width is computed using Stegar's algorithm thus, forming a network skeleton. The process is followed by identifying the network holes by applying dynamic contours and flood fill labelling. However, the method required post-processing and the results reported are qualitative in nature. The method proposed by Anatha et al. [13] determines the presence of pigment network on a block by block basis. Two approaches namely the neighboring gray-level dependence matrix and Laws energy masks were used for detecting the pigment network patterns. Best results were obtained by employing a weighted average of two Laws energy masks thus, obtaining a classification accuracy of 80%.

Grana et al. [14] used Gaussian derivative kernels and Fisher linear discriminant analysis for identification of pigment network masks. A graph based approach was proposed by Sadeghi et al. [15] wherein the image is initially pre-processed using Laplacian of Gaussian filters. The resulting image is converted into cyclic sub graphs corresponding to skin textures, it is followed by filtering and subsequent graph formation for identification of network holes. The pigment network presence/absence is determined by computing the density ratio. Barata et al. [16] employed a set of 64 directional filters with heuristically set parameters for enhancement of pigment network masks, and a trained AdaBoost classifier was used to identify the presence/absence of pigment network masks. However, a constant threshold value was used for the extraction of the enhanced masks. Supervised machine learning and structural analysis were used by Arroyo et al. [17]. The machine learning process generates a set of rules to obtain masks, which are further processed using structural analysis for network masks detection. A similar machine learning approach is reported in [18], wherein probability masks corresponding to pattern's characteristics are generated by fuzzy classification, which is subsequently followed by parameterization and subsequent feature extraction for identification of pigment network masks.

Betta et al. [19] used a combination of region growing, structural and spectral techniques for detection of atypical pigment network patterns. Median filtering and morphological operations were a part of structural techniques, whereas high-pass filtering and Fourier transformation techniques formed a part of spectral techniques. Further Leo et al. [20] performed an update to this study, by adopting a machine learning approach, thereby reporting an approximate classification sensitivity of more than 85%. Sadeghi et al. [21] extracted a set of 69 features from network masks and holes, the masks were generated using the method described in [15]. The features extracted were used to train a boosting classifier, achieving an average classification accuracy of 82.3% on a real-time dataset.

Although, significant contributions have been made by the previously reported studies, there exists a research gap between the current state and desired state in melanoma diagnosis. The shortcomings identified can be broadly categorized into two major categories as follows:

(i) Pertaining to pigment network detection

- Although, pigment network is considered to be a hall mark of malignancy, the state of art studies fail to report the role of pigment network in classification of benign and malignant lesions.
- Lack quantitative validation.
- Report results for two class problems.

(ii) Pertaining to atypical/typical pattern classification.

- Lack of quantitative validation.