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Nevus atypical pigment network distinction and irregular streaks detection in skin lesions images

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***Abstract*— There is no suitable golden standard for the detection of atypical pigment network and irregular streaks applied to skin lesion images. This information however is important in assessment of melanoma in skin dermatoscopic images. Thus there is a need for development of image analysis techniques that satisfy at least subjective criteria defined by dermatologists. In this paper we present the application of histogram based features for detection of atypical pigment network and shape based features supplemented by artificial neural network for detection of irregular streaks. Preliminary test results are promising, for analyzed melanoma images we get 97,7% correctly detected pigmentation networks and 94,8% correctly detected irregular streaks. This paper constitutes the part of our efforts to implement the ELM 7-point checklist in order to support melanoma diagnosis and to automate this process.**

Keywords- malignant melanoma, image processing, irregular streaks, typical and atypical pigment network, 7-point checklist, neural network.

I. INTRODUCTION (HEADING 1)

The malignant melanoma [1] is a malignant tumor of the skin, mucous membranes or the uveitis. It is dangerous because it grows fast and easily metastasizes. Late detection of the malignant melanoma is responsible for 75% deaths associated with skin cancers. Annually over 77 thousand people die from malignant melanoma worldwide. (14-th place in neoplastic disease [2]). This cancer arises from the cells that produce melanin pigment (called melanocytes) and are further transformed into malignant ones. The ultraviolet radiation is considered to be the main cause for the malignant mutation.

Prognosis depends on tumor type and the development of skin lesion inside the tissue. Lesser malignant tumors cure rate is over 90%, when diagnosed early. Due to rapid course of disease, early diagnosis is important factor that increases chances of successful cure. For malignancy evaluation two clinical scales are used: the five-point Clark scale [1] and the four-point Breslow scale [1]. Both scales take into account only the depth of invasion and the evaluation is based on histological material. These hamper the diagnosis because it is not possible and not necessary to remove all nevi. Thus for early diagnosis visual inspection of the skin nevus is performed by trained dermatologist. Such inspection is often supported by technique called epiluminescence microscopy (ELM or dermoscopy) [3]. The dermatologist prepares the diagnosis utilizing one of three popular diagnostics models [4]:

a) the pattern analysis where nevus are classified to different categories based on specific global patterns and combination of local features,

b) the ABCDE-rule which is based on semi-quantitative assessment of four groups of dermatoscopic criteria: asymmetry, border properties, color, diameter and evolution.

c) the ELM 7-point checklist which is a scoring system where the presence of certain structure or pattern has assigned certain score, sum of the scores is base for the diagnosis.

The computer analysis and the image processing are effective tools supporting the quantitative medical diagnosis [5]. Therefore it is desired to develop computer based methods for dermatological images analysis. This can objectify, accelerate and improve the efficiency of melanoma diagnosis.

The idea of implementing abovementioned diagnostic models into computer software is not new. Several papers describing such works can be found. Betta, Di Leo, at all published series of papers [3], [4], [6], [7] describing implementation of ELM 7-point checklist. Smaoui and Bessassi [8] proposed a system utilizing implementation of ABCD rule and ABCD with additional texture and histogram parameters [9]. Jaworek-Koriakowska and Tadeusiewicz in [10] described implementation of Border Irregularity from ABCD rule. Grzymala-Busse, et all described data mining system [11] with ABCD rule addition to increase accuracy. Sathiya et all summarize in [12] contemporary methods for detecting melanoma. Although works concerning recognition melanoma on ELM images were reported none of described systems is close to ideal one. So there is still a room for new developments in this area. In this paper, we present our approach in implementation of the ELM 7-point checklist model. Two of seven criteria are covered, mainly the atypical network and irregular streaks. This work constitutes the continuation of our previous study on the segmentation of images containing skin nevi [13].

The structure of the paper is as follows: the second chapter contains description of analyzed images and the proposed methods; the third chapter presents some tests results and discussion of the proposed method; last chapter sums up the paper.

II. MATERIALS AND METHODS

The material in our work constitutes 98 digital images of skin nevi of two types: malignant melanoma and non-malignant. The images was taken by trained dermatologist. The acquisition system consists of the digital camera (Nikon D90) equipped with the dermatoscope (Heine Delta 20). Images were recorded in the RGB format (16 bits per channel). The resolution of images is 2848 x 4288 pixels. The field of view (FOV) covers area of 10 by 15 mm. Original image files were saved as the Nikon Electronic Format (NEF). For the analysis all files were converted to 8 bit per channel bitmaps. This works deals with two of seven criterion from the ELM 7-point checklist [4]. Those are presence of atypical network and irregular streaks. For the purpose of the work the trained dermatologist identified four subsets:

a) 19 images with the atypical pigment network,

b) 25 with the typical pigmented network,

c) 22 images with irregular streaks,

d) 36 images without irregular streaks,

Examples of such images are shown in Fig. 1.

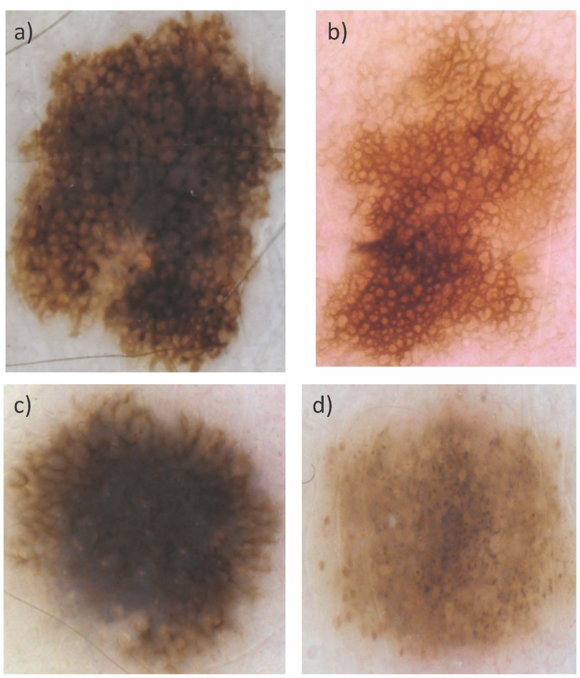

Figure 1. Examples of skin nevi containing between others:
a) the atypical pigmentation network,
b) the typical pigmentation network,
c) irregular streaks, d) no irregular streaks.

The workflow for both criteria consist of following steps:

1. Correction of image illumination,
2. Image segmentation,
3. Feature extraction,
4. Classification.

All images obtained from the acquisition system were affected by the non-uniform illumination introduced by the dermatoscope. The illumination model described in [13] is used to equalize the illumination of the entire image. The semiautomatic image segmentation described in [13] leads to extraction of the nevus region. The feature extraction step is a key difference between workflows used for those two criteria. This step will be explained in details inside two following subsections. The classification is used for decision if the given criterion is met.

A. Recognition of presence of atypical pigmentation network

The atypical pigmentation network is a hyper pigmented or broadened ridges with irregular shape or distribution [4]. Typical pigmentation is more regular and the edges are thinner. To distinguish between two classes of pigmentation network we decided to test vast number texture feature. Those features were calculated for the whole nevus region. We tested over 300 textural features available in MaZda software [14]. Those features base on a region histogram, a co-occurrence matrix [15], a run length matrix, a gradient matrix and an auto regression model. Additionally co-occurrence based features for large offsets up to 60 were calculated by means of MatLab software. Total of 492 textural features was tested. A Fisher coefficient [16] defined in equation (1) and implemented in MaZda was used to choose the best discriminating parameter.

$$F = \frac{D}{V} = \frac{\frac{1}{1-(P_1^2+P_2^2)}2P_1P_2(\mu_1-\mu_2)^2}{P_1V_1 + P_2V_2} \quad (1)$$

where:

D = between-class scatter,

V = within-class variance,

μ = mean of class 1 or 2,

V = variance of class 1 or 2,

P = probability of a given class (defined as the ratio between number of data samples from this class and total number of data samples).

A highest value of Fisher coefficient was obtained for the following features: 90th percentile and 99th percentile estimated from image histogram. Distribution of these features for both classes and classification boundary obtained by means of naive Bayes classifier is presented in Fig. 2.

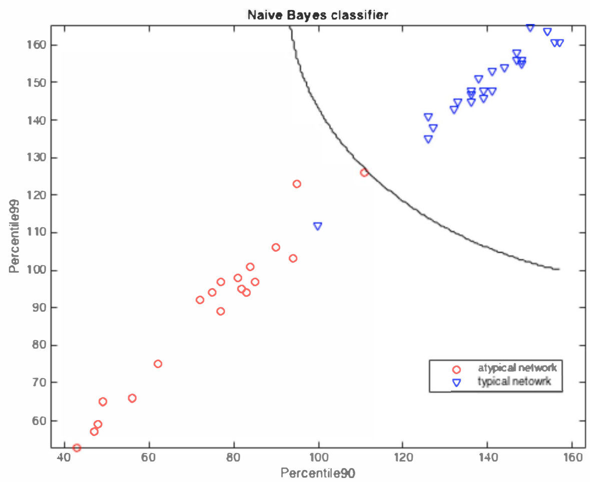

Figure 2. The distribution of test samples on a plane built by means of two best features 90th and 99th percentile. Triangles represents typical pigmentation network and circles represent atypical pigmentation network. Black solid line shows classifier decision.

One can see that usage of the sole 90th percentile and a threshold classifier will led to the classification with only one sample misclassified.

B. Recognition of irregular streaks

Irregular streaks have appearance of radially and asymmetrically arranged linear extensions at the edge of the lesion. For such structures we decided to test shape/edge related features such as the solidity [17], the convexity [17] and region based features as the entropy [18]. We also tested parameters based on the distance between the contour of the nevus and its contour obtained for the circumscribed convex hull [18] (as shown in Fig. 3).

The nevus contour, the convex hull and the center of mass are calculated based on the lesion region obtained during the segmentation, as described in [13]. Then for each radius that

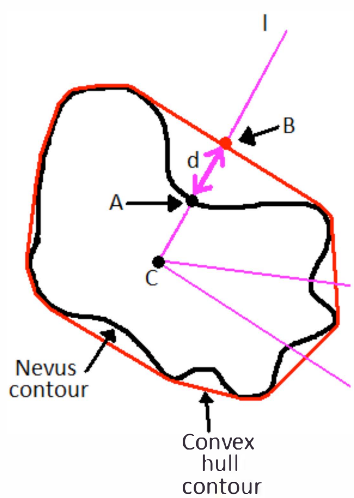

Figure 3. Distance distribution measurement. The difference in distance between the contour of the nevus (point A) and contour of the convex hull (point B). Point B is identified as a point on the contour of the convex hull along the line connecting the center of the mas (point C) with analized point A on the contour of the nevus

connects center of mass and contour points (A in Fig. 3) the cross-section with the convex hull is found (B in Fig. 3). Based on the estimated Euclidean distance (d in Fig. 3) a number of statistical parameters are calculated. These are mean, standard deviation, variance, skewness [19] and kurtosis [19]. Distribution of *d* as a function of histogram bins is showed in Fig. 4. Distribution of *d* within data set of nevus without irregular streaks is show on Fig. 4a, and with irregular streaks is shown in Fig. 4b.

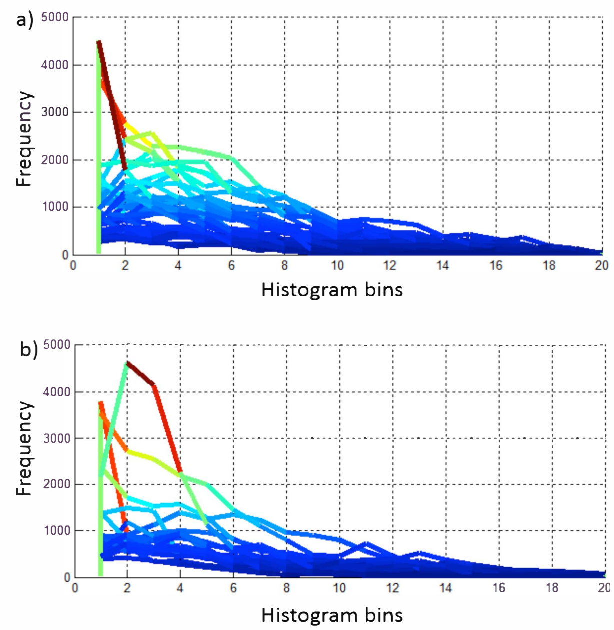

Figure 4. Distribution of distances in function of histogram bins for data set, a) nevus without irregular streaks, b) nevus with irregular streaks

We tested different combinations of features and different classifiers. Best result were obtained for four features (solidity, convexity, entropy and skewness based on distance between contours) processed by two layer ANN [20] (Fig. 5) having two neurons in hidden layer implemented in MaZda software [14].

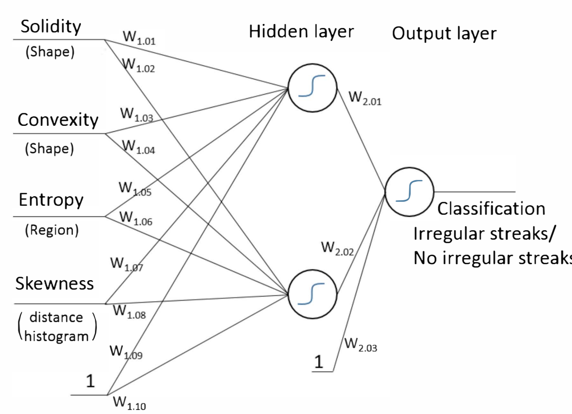

Figure 5. Artificial Neural Network used for evaluation

III. Results and Discussion

By means of proposed approach we are able to correctly discriminate between typical and atypical pigmentation network in all but one test cases. This is an averaged result of 5-fold cross-validation of Bayes classifier. Mean classification error was 2.3%. Mean sensitivity and specificity of proposed method were 95% and 100%, respectively.

The incorrectly classified example is shown in Fig. 6 where appearance of both networks in the networks area is noticeable.

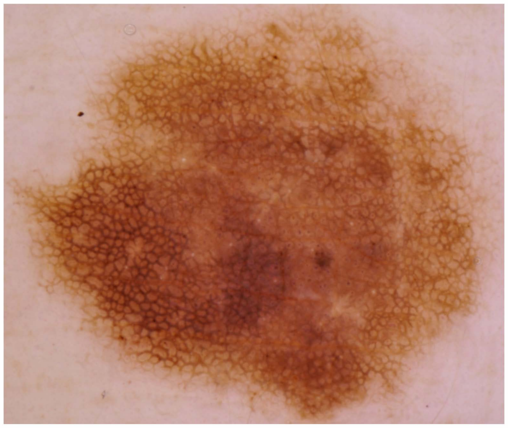

Figure 6. Test image for with nevus containing typical pigmentation network was classified as nevus with atypical.

Proposed method for the identification of irregular streaks with the use of ANN allows for correct discrimination of 55 out of 58 examples. This gives classification error on the level of 5.17%. Sensitivity of proposed method was 91% and specificity of 97%. Presented results are obtained for the training data set. This was caused by not sufficient number of data (amount of test images) to test the network on an independent data set. Network validation will be performed after acquisition of larger number of skin images.

Three cases of misclassified nevi are shown in Fig. 7. In two cases segmentation was responsible for misclassification. In those images irregularities had shape of pulled globules (Fig.7.a), and there was a need to perform opening and closing operations to get rid of small areas inside segmented mask (Fig.7.b). In the third case the mole was a different type mark (Fig.7.c).

The proposed methods were compared with results reported in [4], where in detection of the atypical pigmentation network has sensitivity of 80% and specificity of 82%, and for irregular streaks detection sensitivity of 86% and specificity of 88% were achieved. Results side by side are presented in Table I.

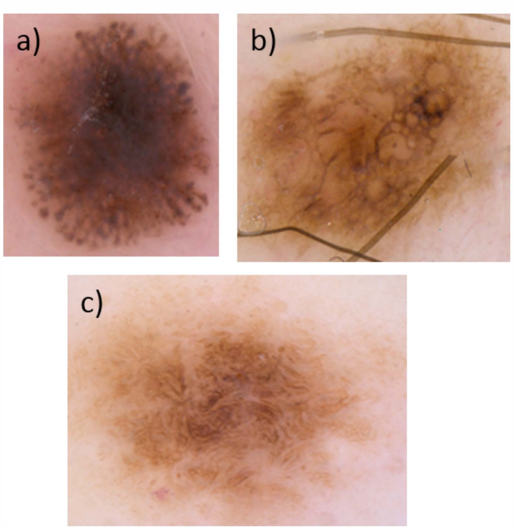

Figure 7. Misclassified lesion examples

TABLE I. Results compared to other works

	Atypical network		Irregular streaks	
	Our approach	Competitive approach	Our approach	Competitive approach
Sensitivity	95%	80%	91%	86%
Specificity	100%	82%	97%	88%

IV. Summary

In this work we presented implementation of identification of two out of seven structures from the ELM 7-point checklist for diagnosis melanocytic nevi. Proposed approach shows slightly better results to other approaches reported in literature. We will continue our work in order to cover all seven criteria and create a system supporting diagnosis of the malignant melanoma.

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