No-reference Blur Assessment of Dermatological Images Acquired via Mobile Devices

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Abstract. One of the most important challenges of dealing with digital images acquired under uncontrolled conditions is the capability to assess if the image has enough quality to be further analyzed. In this scenario, blur can be considered as one of the most common causes for quality degradation in digital pictures, particularly in images acquired using mobile devices. In this study, we collected a set of 78 features related with blur detection and further analyzed its individual discriminatory ability for two dermatologic image datasets. For the dataset of dermoscopic images with artificially induced blur, high separation levels were obtained for the features calculated using DCT/DFT and Lapacian groups, while for the dataset of mobile acquired images, the best results were obtained for features that used Laplacian and Gradient groups.

Keywords: Mobile image assessment, dermatology, blur distortion, feature extraction.

1 Introduction

The fast spreading of this new generation of mobile devices, with remarkable improvements in terms of image acquisition, opens up the possibility of development of new mobile-based approaches for healthcare, with easy data transmission and that can be used regularly by the patients. In this scope, Dermatology appears as an interesting case study for this kind of approach due to the significant importance of the visual inspection in the clinical practice for pre-diagnosis and follow-up of specific skin related problems.

In terms of clinical practice in dermatology, the currently most accepted method for image acquisition involves the usage of dermoscopy, a diagnostic technique for the observation of skin lesions with optical magnification and polarized lightning [1]. When compared to dermoscopy, the images acquired with a smartphone built-in camera may contain several additional artifacts which will have impact in terms of image quality, like motion and defocus blur. Due to this reason, it is important to infer about reliable methods to evaluate the blur distortion of smartphone acquired images for dermatological purposes.

Image quality assessment (IQA) measures can be divided into two categories: subjective or objective [2,3]. The first category of methods involves human observers to evaluate image quality whereas the latter determines an objective

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quality score. Due to its nature, subjective methods can easily turn fastidious, time consuming and expensive, consequently preference is given to search for objective methods capable of quickly analyze images and report their quality without human involvement.

Depending on the presence of a reference image, objective methods are classified into full reference, reduced reference or no reference approaches [2,3]. In the full reference approaches, the processed image is compared to a reference such as the original image; in the reduced reference approaches, only partial information of the original image is available and it is described by a set of features; at last, in the no reference approaches the absolute value is based on the characteristics of the given image. Considering the no-reference category, innumerous measures have been proposed along the years to assess image quality, and more specifically concerning blur distortion. In this work, and following other studies [4], these measures can be classified into five broad groups according to their working principles: Gradient based, Laplacian based, Statistical based, DCT/DFT based and Other principles.

Regarding systems to evaluate the quality of images acquired from smartphones, the literature is scarce, and inexistent if we focus on its applicability for dermatological purposes, to the best of our knowledge. In [5] the authors presented a blurred image detection system for mobile devices, based on the Bayes discriminant function and the statistics of the magnitude of the image gradient. Recently, [6] developed two methodologies extension for blur detection in camera-captured document images: the first one based on the Local Power Spectrum and the second based on eigen analysis, proving to have better performance than the first one for document images.

The structure of this paper is as follows. Section 2 describes the datasets used in this work. Section 3 defines the methodology followed, with detailed description of the feature extraction and feature analysis steps. Section 4 shows the obtained results. Finally, Section 5 gives the conclusions and future work.

2 Datasets

Our study intends to assess the quality of dermatological images obtained from mobile devices regarding its level of focus. Based on what is known, there is no publicly available image quality database that includes dermatological images, so we have used 2 different dermatological databases: the PH^2 dataset and the IPO Mobile dataset. With this, we aim to test the capability of our approach to detect blur induced artificially with the first dataset and blur resulting from the normal image acquisition process using a smartphone with the second dataset.

2.1 PH^2

This database contains a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi and 40 melanomas. The dermoscopic images were collected at the Dermatology Service of Hospital Pedro Hispano

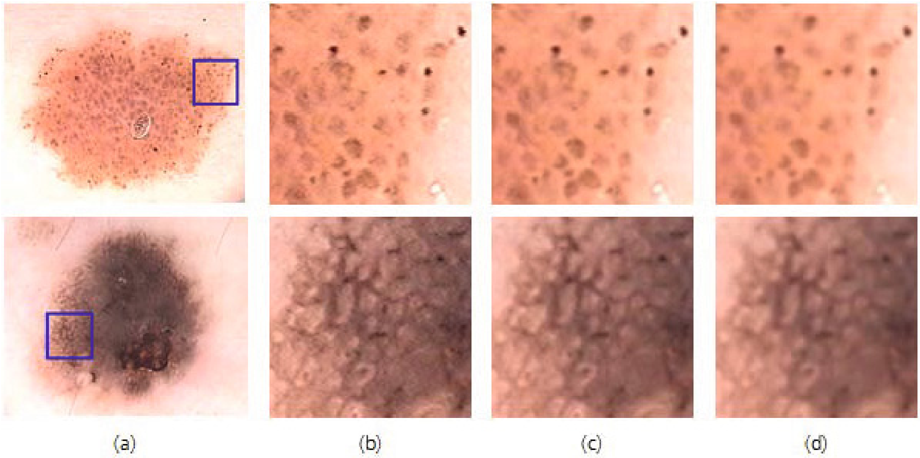

Fig. 1. Examples of two images from the PH^2 dataset: (a) original images; (b) detail of the original images; blurred images with sigma of 0.65 (c) and 1 (d)

(Matosinhos, Portugal) under the scope of the project ADDI [7]. The images are 8-bit color images with 768x560 pixels of resolution, acquired using the Tuebinger Mole analyzer system with a magnification of 20x.

All the images in this dataset can be considered focused, since they were acquired under well controlled and constant conditions. In order to assess the capability of the proposed approach to detect artificially blurred images, 400 distorted images were artificial created by applying a Gaussian blur with window size of 11, and sigma of 0.65 and 1 (Fig. 1). The values used for distorting the images are according to the reference values used in other reference databases available online [3].

2.2 IPO Mobile

This database was collected at the Portuguese Institute of Oncology of Porto (IPO), under the scope of the project Melanoma Detection [8]. The images were acquired during 4 appointments with 2 dermatologists, where the project was previously explained to the patients and the statement of agreement obtained. The database contains a total of 90 images, that correspond to 80 different skin moles, obtained from 31 subjects (14 males and 17 females) with ages between 28 and 70 years (mean age 43 years). They are 8-bit color images with 652x652 pixels of resolution, acquired with a mobile phone Htc One S.

Each image of the dataset was later manually classified as focused or blurred by 5 subjects independently. The images were labeled according to the most voted class, which gave a total of 54 focused images and 36 blurred images (Fig. 2).

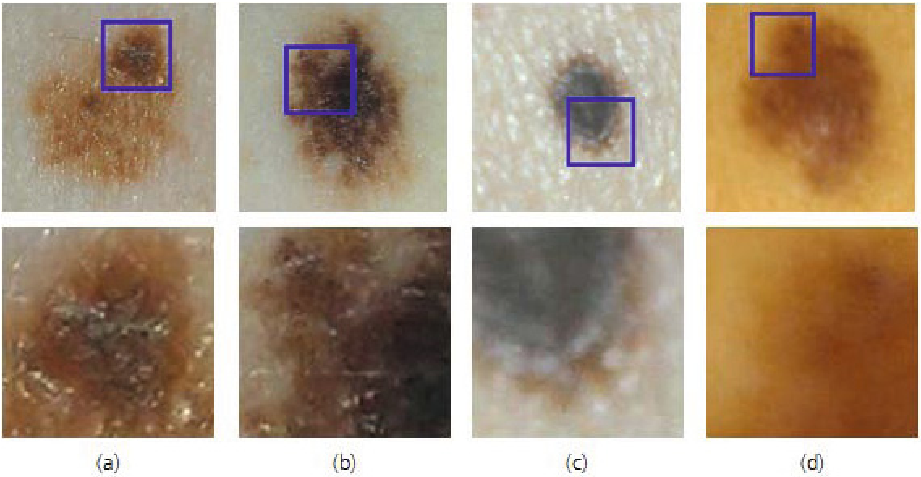

Fig. 2. Example of four images from the IPO Mobile dataset and respective details: (a) and (b) Focused images; (c) and (d) Blurred images

3 Methodology

The proposed methodology comprises 2 main blocks: Feature Extraction and Feature Analysis.

3.1 Feature Extraction

In terms of the extracted features, we used a set of algorithms previously referred on the literature for blur detection, as well as other algorithms still not used to this purpose, to the best of our knowledge. Table 1 summarizes the considered algorithms and all the related measures calculated from them. Several measures were extracted for each algorithm (e.g. sum, mean, standard deviation, minimum and maximum value). The underlined measures in Table 1 correspond to those that already have been referenced on literature for blur detection purposes. In most of the cases, we verified that the measure corresponding to minimum value was zero to all images, so it was discarded from the study. The referred features were computed in C++ using the OpenCV library [9].

3.2 Feature Analysis

To compare the discriminatory abilities of the features between focused and blurred images, we used the θ measure, a non-parametric measure used to characterize the degree of separation of two distributions. This measure was obtained through U/mn, meaning, the Mann-Whitney U statistic divided by the product of the two samples. This normalized statistic ranges between 0 and 1, with values near 0.5 indicating similar distributions and values near 1 indicating strong

Table 1. Summary of the features extracted for blur detection

Group	Abbr.	Name	refs	Measures
Gradient based	GRAE	Energy Image Gradient	[11,12]	Sum, mean, std, max
	GRAS	Squared Gradient	[13,14]	Sum, mean, std, max
	TENG	Tenengrad	[15,16]	Sum, mean, std, max, var
Laplacian based	LAPE	Energy of Laplacian	[11,12]	Sum, mean, std, max
	LAPSM	Sum Modified Laplacian	[17]	Sum, mean, std, max
	LAPD	Diagonal Laplacian	[18]	Sum, mean, std, max
	LAPV	Variance of Laplacian	[16]	Mean, std, max, var
	LAPG	Laplacian and Gaussian	[19]	Sum, mean, std, max
Statistical based	GLVA	Gray Level Variance	[15]	Sum, mean, std, min, max, var
	GLVN	Norm. Gray L. Variance	[14]	Normalized variance
	HISE	Histogram Entropy	[20]	Sum (R, G, B, gray)
	HISR	Histogram Range	[20]	Range (R, G, B, gray)
DCT/ DFT	DCT	DCT	[21]	Sum, mean, std, min, max
	DFT	DFT	[22]	Sum, mean, std, min, max
Other principles	BREN	Brenner's Measure	[14]	Sum, mean, std
	CURV	Image Curvature	[23]	Sum, mean, std, min, max
	SPFQ	Spatial Freq. Measure	[13]	Sum, mean, std, max
	VOLA	Vollath's autocorrelation	[14]	Sum, mean, std, max
	PRCB	Perceptual blur	[24]	Count and mean (horizontal and vertical)

separation. In order to simplify the comparison, we ranked the features by means of their discriminatory ability evaluated by max(U/mn, 1-U/mn)[10].

4 Results

Table 2 shows the 10 best ranked features for the two datasets separately, based on their discriminatory ability between blurred and focused images. The discriminatory indexes were evaluated by max(U/mn, 1-U/mn), thus ranging between 0.5 and 1. The results demonstrate high discriminatory ability for the DCT/DFT group, followed by the Laplacian group when using the PH^2 dataset, with dermoscopic images. For the IPO Mobile dataset, the best results come from the Laplacian group as well as the Gradient group. It should be also noted that the 10 best ranked features for each dataset significantly differs. This difference can be explained by the different nature of the blur distortion in each used dataset, being artificially induced and resulting of the normal mobile image acquisition process, in the PH^2 and IPO Mobile dataset, respectively. Thus, one can conclude that the subset of features with best discriminatory ability will considerably depend on the nature of the blur distortion in the considered images.

Figure 3 shows the data distribution of four features for each dataset, two with high ranking and two with low ranking, which illustrates the discriminatory ability of those features for blur detection. It is worth noting that the level of separation of the high ranked features for each datasets clearly varies in terms of data distribution, existing a stronger separation for the PH^2 dataset. Once again, it should be taken into account the artificial nature of the blur present in the PH^2 dataset, being more homogeneous along the entire image, and consequently explaining the best data separation of those features when compared with the IPO Mobile dataset.

Table 2. Summary of the best ranked features for the PH^2 and IPO Mobile datasets, using max(U/mn, 1-U/mn)

	PH^2		IPO Mobile	
Ranking	Index	Feature	Index	Feature
1	0.9998	DFT_mean	0.9172	VOLA_max
2	0.9996	DFT_sum	0.9156	LAPD_max
3	0.9995	DFT_std	0.9151	LAPE_std
4	0.9993	LAPSM_sum	0.9059	LAPD_std
5	0.9993	LAPSM_mean	0.9038	TENG_std
6	0.9989	PRCB_my	0.9038	TENG_var
7	0.9980	LAPE_mean	0.9023	TENG_max
8	0.9980	LAPV_std	0.8997	GRAS_std
9	0.9980	LAPV_var	0.8997	LAPG_std
10	0.9978	LAPE_sum	0.8987	LAPE_max

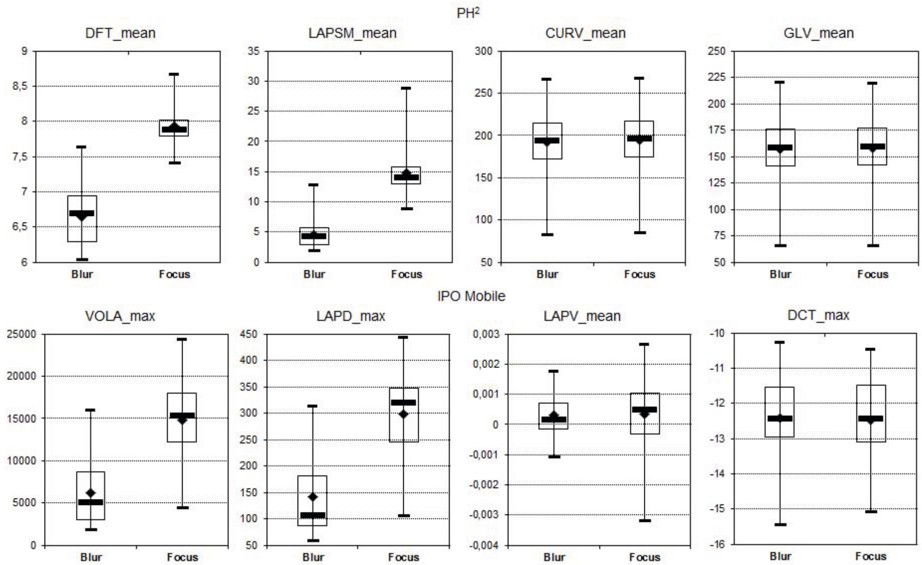

Fig. 3. Data distribution for PH^2 and IPO Mobile datasets of four features, where the two first columns depict features with high ranking and the last two columns show features with low ranking

5 Conclusions and Future Work

The development of new mobile-based approaches for healthcare combined with the importance of visual inspection in the dermatological field lead us to infer about reliable methods to assess the image quality of smartphone acquired images for dermatologic purposes, especially regarding the blur distortion.

In this study, we collected a set of 78 features related with blur detection and analyzed its individual discriminatory ability for two different dermatologic image datasets using the Mann-Whitney U statistic. Taking into consideration the results obtained, one can confirm that several of the computed features are capable of successfully discriminate blurred images from focused images. Furthermore, one can conclude that the subset of features with best discriminatory ability considerably depends on the nature of the blur distortion in the considered images.

The analysis of the data distribution for each individual feature can be useful for feature selection purposes, but it should also be taken into account the existence of important relationships between features that might allow achieving better classification results. For instance, one feature may have a low discriminate power when used by itself, but be very useful when combined with other features. Thus, as future work, the authors intend to extend this study by evaluating the impact of the application of feature selection methods, as well the application of different classification methods to obtain a robust methodology for the automatic detection of blurred images from images acquired from mobile devices, especially designed for dermatological purposes.

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