Chapter 28
Retinal Image Quality Assessment Using Shearlet Transform

E. Imani, H.R. Pourreza, and T. Banaee

28.1 Introduction

Eye diseases such as diabetic retinopathy (DR) affect a large number of the population. Retinal fundus photographs are widely used in the diagnosis and treatment of various eye diseases in clinics. It is also one of the main resources for mass screening of diabetic retinopathy. The resulting retinal images must be examined by an expert human grader in a cumbersome and time-consuming diagnosis process. Automated analysis and diagnosis has the potential to reduce the workload and thus increase the cost-effectiveness of such screening initiatives. Nevertheless, there are number of problems that must be solved in order to develop a fully reliable automated retinal images analysis system. Among them, is the need to guarantee that the quality of the retinal images to be graded exceeds a threshold below which the automated analysis procedures may fail [PiOlDa12].

In a DR system, an image is considered poor quality if it is difficult or impossible to make a reliable clinical judgment on the image regarding presence or absence of DR [YuEtAl12]. Performing automated analysis on the image of insufficient quality will produce unreliable results. Images with low quality should be examined by an ophthalmologist and reacquired if necessary [NiAbVa06]. The store and forward teleophthalmology systems involve acquiring images and transmitting them for remote retinopathy detection. This could become problematic when received images do not have enough quality and patient is not accessible. Thus an algorithm

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C. Constanda, A. Kirsch (eds.), *Integral Methods in Science and Engineering*,
DOI 10.1007/978-3-319-16727-5_28

with ability of automatically assessing fundus image quality is a necessary tool in preprocessing stage for reliable lesion detection especially in the systems that deliver eye care through telecommunications technology.

Fundus image quality can be affected by a number of factors including patient's head or eye movement, poorly dilated and small pupils, blinking and media opacity. Head or eye movement can result in out-of-focus and incorrectly illuminated images. Poorly dilated pupils may affect image illumination and create dark low-contrast images that can prevent lesion identification. If fundus cameras capture retinal images through cataract, images appear blurred and are often poor quality [HuEtAl11]. In 2006, Zimmer–Galler [ZiZe06] reported that 11% of the images in their study were unreadable. It was estimated that 25% of the poor quality images were caused primarily by poor patient fixation, 25% by poor focus and pupil centering, and 25% were thought to be caused by small pupil size, media opacity, and instrument failure. A specific cause for the unreadable image could not be determined for the remainder. Figure 28.1 shows some instances of good and poor quality retinal images.

Several approaches have been developed to automatically determine the quality of the retinal images. These approaches could be classified into two categories. The first category is based on generic image quality parameters such as sharpness and contrast. These methods make use of simple image measurements to estimate image quality avoiding eye structure segmentation procedures which are usually complex and time-consuming tasks [PiOlDa12]. In 2001, Lalondey [LaGaBo01] proposed a method based on histogram of edge magnitude and local histogram of pixel gray-scale values to evaluate image focus and illumination. In this method, the quality of a given image is determined through the difference between its histogram and the mean histogram of a set of good quality images used as reference. In 2009,

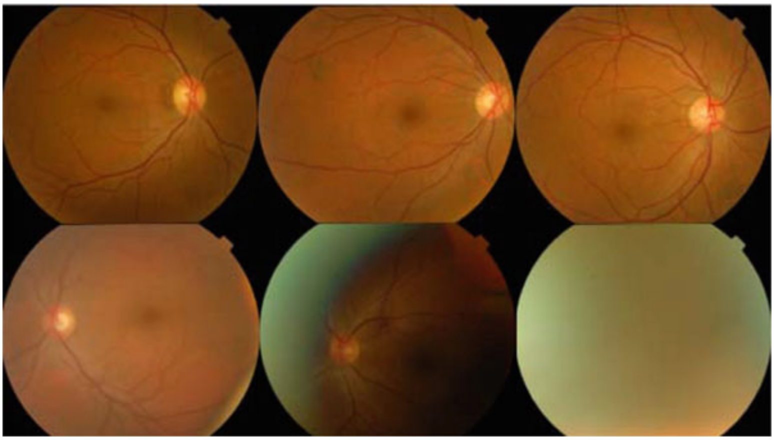

Fig. 28.1 Examples of good quality and poor quality retinal images: top row are good quality images and bottom row are poor quality images

Davis et al. [DaEtAl09] focused their quality assessment on contrast and luminance features. A method based on sharpness and illumination parameters was proposed by Bartling [BaWaMa09] in 2009. Illumination was measured through evaluation of contrast and brightness and the degree of sharpness was calculated from the spatial frequencies of the image. Image structure clustering, Heralick features, and sharpness measures based on image gradient magnitudes were used by Paulus et al. [PaEtAl10] to classify poor quality retinal images. In 2012, Dias et al. [PiOlDa12] introduced a method based on fusion of generic image quality indicators such as image color, focus, contrast, and illumination.

The advantage of the image quality assessments based on generic image quality measures is their algorithmic simplicity which translates into reduced computational complexity [PiOlDa12].

The second group is based on the structural information of the image which requires segmentation of anatomical landmarks in retinal images. In 2005, Fleming et al. [FlEtAl06] developed a method based on field definition and image clarity. The clarity analysis is based on the vasculature of a circular area around the macula. The authors whether or not a given image has enough quality using presence/absence of small vessels in the selected circular areas. In 2006, Niemeijer [NiAbVa06] proposed a method based on clustering the filter bank response vectors in order to obtain a compact representation of the image structures. In 2008, Giancardo et al. [GiEtAl08] assessed the quality of retinal images based on the eye vasculature. Giancardo concluded used vessel density in local patches as a feature vector for quality assessment. In 2011, Hunter et al. [HuEtAl11] proposed a method based on the clarity of retinal vessels within the macula region and contrast between the fovea region and retina background. The methods based on structural information require anatomical landmarks segmentation which is complex and error prone, especially in the case of poor quality images. This is the major disadvantage of such approaches [PiOlDa12].

The rest of the chapter is organized as follows. In Section 28.2, we give a brief introduction to shearlet transform. In Section 28.3, we propose a retinal image quality assessment based on generic parameters with the usage of shearlet transform. We evaluate the performance of the developed approach in Section 28.5. The results are compared against state-of-the-art retinal image quality assessment methods. In Section 28.6, we finish the paper with some conclusions.

28.2 Prerequisites

One of the most useful features of wavelets is their ability to efficiently approximate signals containing pointwise singularities. Consider a one-dimensional signal which is smooth away from point discontinuities. If the signal is approximated using the best M-term wavelet expansion, then the rate of decay of the approximation error, as a function of M, is optimal. In particular, it is significantly better than corresponding Fourier approximation error [Li10]. Since wavelets have isotropic supports, they fail to capture the geometric regularity along edges. Recently, the novel directional representation system of shearlets [LaEtAl05] proposed to provide efficient tools for analyzing the geometrical structures of a signal using anisotropic window functions. Among directional representation systems, shearlets are the most versatile and successful systems, the reason for this being an extensive list of desirable properties: shearlet systems are generated by one function, they provide precise resolution of wavefront sets, they allow compactly supported analyzing elements, they are associated with fast decomposition algorithms, and they provide a unified treatment of the continuum and the digital realm [KuLeLi12].

28.2.1 Brief Introduction to Shearlet Transform

In many applications in image processing, the important information is often located around edges separating image objects from background. These features correspond to the anisotropic structures in the image. Shearlets are designed to efficiently encode such anisotropic features [KuLeLi12]. For $j \geq 0, k \in Z$, let

$$A_{2^j} = \begin{pmatrix} 2^j & 0 \\ 0 & 2^{\frac{j}{2}} \end{pmatrix} \quad S_k = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix} \quad M_c = \begin{pmatrix} c_1 & 0 \\ 0 & c_2 \end{pmatrix}$$

where $c = (c_1, c_2)$ and c_1, c_2 are positive constants. Similarly,

$$\tilde{A_{2^j}} = \begin{pmatrix} 2^j & 0 \\ 0 & 2^{\frac{j}{2}} \end{pmatrix} \quad \tilde{S_k} = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix} \quad \tilde{M_c} = \begin{pmatrix} c_1 & 0 \\ 0 & c_2 \end{pmatrix}$$

We are now ready to define a shearlet transform as follows. Let $c = (c_1, c_2) \in (R_+)^2$. For $\phi, \psi, \tilde{\psi} \in L^2(R^2)$ the cone-adapted discrete shearlet system $SH(\phi, \psi, \tilde{\psi})$ is defined by

$$SH(\phi, \psi, \tilde{\psi}; c) = \Phi(\phi; c_1)\Psi(\psi; c)\tilde{\Psi}(\psi; c)$$

where

$$\Phi(\phi; c) = \{\phi_m = \phi(. - m) : m \in Z^2\}$$
$$\Psi(\psi; c) = \{\psi_{j,k,m} = 2^{3j/4}\psi(S_k A_{2^j}. - m) : j \geq, |k| \leq \lceil 2^{j/2} \rceil, m \in M_c Z^2\}$$
$$\tilde{\Psi}(\tilde{\psi}; c) = \{\tilde{\psi}_{j,k,m} = 2^{3j/4}\tilde{\psi}(\tilde{S}_k \tilde{A}_{2^j}. - m) : j \geq, |k| \leq \lceil 2^{j/2} \rceil, m \in M_c Z^2\}$$

If $SH(\phi, \psi, \tilde{\psi}; c)$ is a frame for $L^2(R^2)$, we refer to ϕ as a scaling function and ψ and $\tilde{psi}$ as shearlets. Observe that shearlets are obtained by applying translation, anisotropic scaling matrices A_{2^j} and shear matrices S_k to the fixed generating

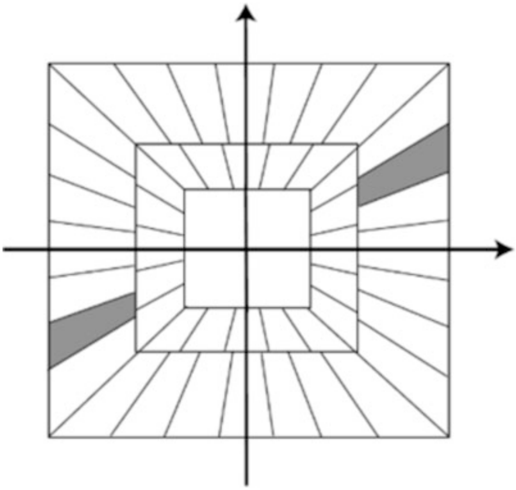

Fig. 28.2 The tilting of the frequency plane introduce by shearlets in Ψ.

functions ψ . The matrices A_{2j} and S_k lead to windows which can be elongated along arbitrary directions and the geometric structures of singularities in images can be efficiently represented using them [Li10]. Figure 28.2 shows the tilting of the frequency plane using shearlet system ψ. It was shown that shearlet ψ can provide nearly optimal approximation for a piecewise smooth function f with C^2 smoothness except at points lying on C^2 curves [Li10].

28.3 Proposed Method

In this work, an automated retinal image quality assessment system is presented. Input to the developed system is a color image of human retina, which is acquired by using a fundus camera, and its output is the quality level of the input image, as shown in Figure 28.3. The proposed method follows a sequences of steps: preprocessing, feature extraction, and classification. In preprocessing step, we remove useless image information in order to decrease the processing time and the green channel of the retinal image selected for further processing. In the second step, we extract generic features with the usage of shearlet transform. Finally by using these features and a supervised classifier, we specify whether the image is of poor or good quality. In this section, the proposed algorithm is described in detail.

28.3.1 Preprocessing

Since green channel of the image provides maximum contrast for retinal landmarks such as vessels among other color image components, this channel is chosen to

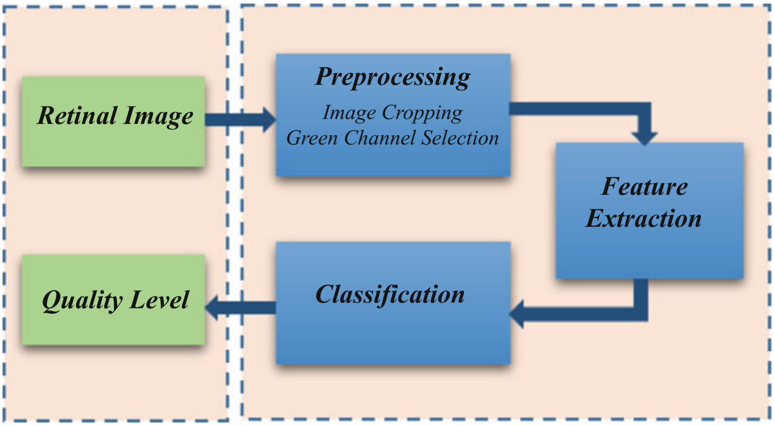

Fig. 28.3 Block diagram of the proposed method

apply the proposed algorithm. We remove useless information of the retinal image by cropping it in order to include retinal region only. A mask for cropping the retinal image is created using a threshold value and morphological operations. The binary mask is created by applying a threshold value of 3 to green plane of the retinal images. Afterwards, noisy regions on the background and foreground are removed using morphological opening and closing. After creating the retinal mask, we find the bounding box containing the retinal region. Cropping the useful part of retinal image accelerates other processing stages. Finally, the images are resized to 512×512 pixels.

28.3.2 Feature Extraction

Visual perception is very sensitive to local image structures such as edges. The quality of the image is a function of edge strength. In blurred and low contrast images, the strength of edges is very weak. Thus evaluation of retinal image quality can be made by edge features. In retinal images, these edges arise from vasculature, optic disk, and lesions. The proposed method assesses the quality of retinal images using edge information. The edge features correspond to the anisotropic structures in the data. Since shearlet systems capture such anisotropic features efficiently [KuLeLi12], we use shearlet transform to detect retinal edge features. The degree of image quality could be specified by measuring the alterations in the statistical characteristics of the shearlet coefficients.

We classify retinal images as good quality or poor quality. Some instances of poor quality retinal images are shown in Figure 28.1. As it is shown in this figure, the strength of the edges in poor quality images is lower than good quality ones. Thus, the image quality level can be specified by measuring the changes in statistical characteristics of the edge information. The retinal image is decomposed using shearlet transform. Each coefficient in shearlet expansion of an image is the result of convolution of the associated shearlet and the image. If a shearlet of a given scale, angle, and location is approximately aligned along a curve, its shearlet coefficient is large, otherwise it is close to zero [KuSa07]. Since changes in image quality level affect the property of curve singularities in the image, the corresponding large shearlet coefficients will be also affected. Hence, the quality of retinal image could be assessed using statistical characteristics of shearlet coefficients.

In order to demonstrate that sub-band statistics are affected by changing in quality levels of the image, Figure 28.5 plots the coefficients distribution of good and poor quality retinal images which were shown in Figure 28.4. As it has been indicated in Figure 28.5, the coefficients distribution of the poor quality retinal

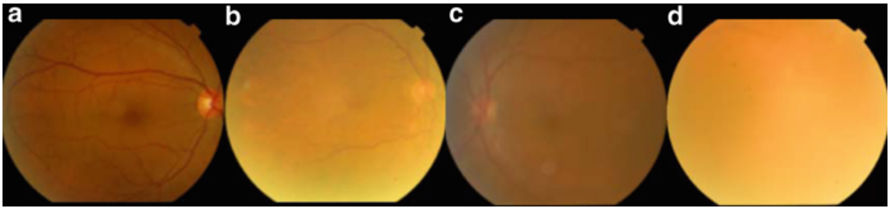

Fig. 28.4 Some instances of retinal images with different quality level. **(a)**: a good quality retinal image. **(b-d)**: poor quality retinal images.

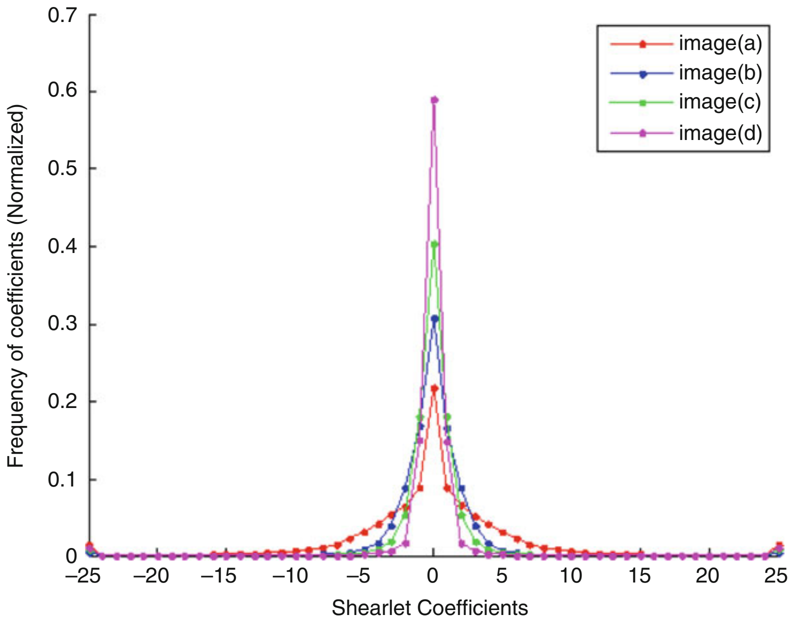

Fig. 28.5 Shearlet coefficients distribution of retinal images.

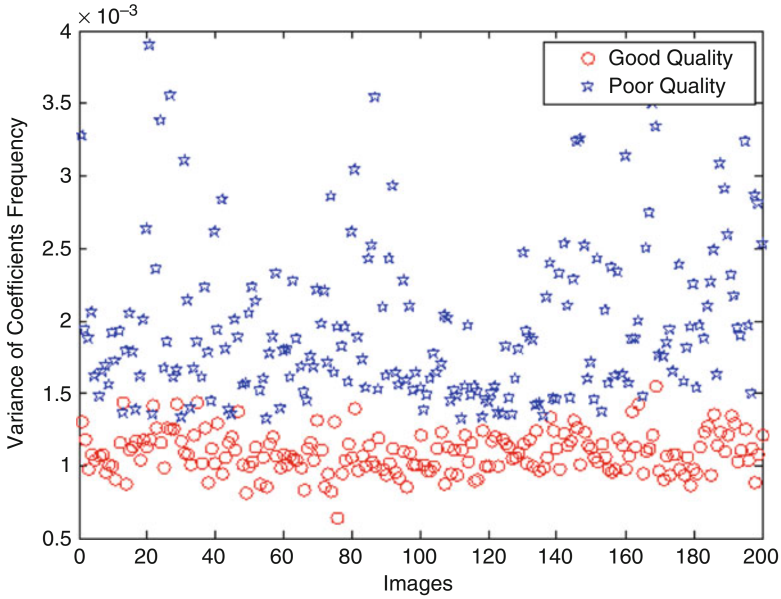

Fig. 28.6 VSCF values of 400 retinal images with different quality level.

images is more concentrated around zero and falls rapidly. The Variance of the Shearlet Coefficients Frequency (VSCF) is computed to evaluate the quality of the images. By decreasing the quality level of image, the value of VSCF increases. In order to demonstrate the effect of quality level on the VSCF value, Figure 28.6 shows the value of VSCF for 400 images with 200 good quality and 200 poor quality. As it can be seen from Figure 28.6, the VSCF values for good quality retinal images are less than VSCF values for poor quality ones. Thus, VSCF value could be used to classify retinal images as good quality or poor quality.

The images are decomposed into three scales and 8 orientations to form oriented responses. Since the finer scales are more sensitive to noise, the coefficients of the second scale of shearlet transform are used to extract statistical features.

28.4 Material

Several retinal image datasets were used to develop and test the retinal image quality assessment. All of the images have been manually graded by ophthalmologists from the Khatam-Al-Anbia eye hospital of Mashhad, Iran, using a software tool provided for image annotation.

28.4.1 Messidor Dataset

The images in this dataset were obtained using a color video 3CCD camera on Topcon TRC NW6 non-mydriatic retinograph with a 45 degree field of view. The dataset consists of 1200 eye fundus color images with the size of 1440×960, 2240×1488 or 2304×1536 pixels.

28.4.2 Khatam-Al-Anbia Dataset

Khatam-Al-Anbia dataset were obtained in Khatam-Al-Anbia eye hospital of Mashhad, Iran. This dataset includes 1000 retinal images with the resolution of 3872×2592 pixels.

28.5 Results

This section presents the classification results of the image quality assessment algorithm. The retinal images are classified as good quality and poor quality using a supervised classifier and extracted feature vector. A support vector machine (SVM) with different kernels was used as a classifier. Classifier testing was performed by 5-fold cross validation, using 80% of the dataset for training and 20% of the dataset for testing. In order to assess the algorithm performance, three measures were used: sensitivity, specificity, and accuracy. These performance measures are defined as follows:

$$sensitivity = \frac{TP}{TP + FN}$$

$$specificity = \frac{TN}{TN + FP}$$

$$accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively. The results of the retinal quality assessment using SVM classifier with different kernels on Messidor and Khatam-Al-Anbia datasets are shown in Table 28.1 and Table 28.2. As it is shown in Table 28.1, the best results are obtained using rbf and polynomial kernels on Messidor and Khatam-Al-Anbia datasets. Table 28.3 compares the performance of the proposed method with the method presented in [NiAbVa06], in terms of sensitivity, specificity on Messidor dataset. Results of Niemeijer et al. [NiAbVa06] is provided by the authors. The results show that the performance of the proposed method is higher than this algorithm.

Table 28.1 Performance achieved by the proposed method on Messidor dataset.

	sensitivity	specificity	accuracy
linear	96.00	93.59	93.58
quadratic	96.00	92.83	92.83
polynomial	92.00	93.17	93.08
rfb	96.00	93.76	93.75

Table 28.2 Performance achieved by the proposed method on Khatam-Al-Anbia dataset.

	sensitivity	specificity	accuracy
linear	96.34	97.46	96.90
quadratic	96.72	97.26	97.00
polynomial	97.15	96.69	96.90
rfb	96.34	97.46	96.90

Table 28.3 Performance achieved by the proposed method and Neimeijter et al method.

	sensitivity	specificity
Proposed Method	96.00	93.76
Niemeijer et al. Method	84.44	90.73

28.6 Conclusions

The proposed method evaluates the retinal image quality with the usage of shearlet transform. Changes in quality level of the retinal image affect the properties of image edges. Therefore, edge information for the images could be used to assess their quality. The edge and curve information of the image are detected using shearlet transform. Image quality levels were specified by measuring the alterations of the statistical characteristics of shearlet coefficients. Experimental results have shown that the proposed method gives comparable results (93.75% for Messidor and 96.90% for Khatam-Al-Anbia) on Messidor and Khatam-Al-Anbia datasets.

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