Image Quality Assessment for the Visually Impaired

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Abstract. In recent years, image enhancement methods have been developed to assist visually impaired people in the everyday life. These methods are promising but they currently suffer from the problem of their correct adjustment according to the specificities of each patient. To address such a problem, an objective quality metric could be used to quantify if enhancement schemes do not introduce artifacts that could be perceived as troublesome by visually deficient persons. As all existing metrics were designed to assess the image quality for observers with normal or corrected to normal vision, they are not appropriate in the context of low vision. Then an alternate framework is presented in this paper. This framework combines three distinct quality attributes that were identified as important features for the visually impaired in image quality assessment and it has been developed to adapt to the different types of visual pathologies.

Keywords: visual aid, quality metric, image enhancement, low vision.

1 Introduction

According to the most recent report published by the World Health Organization (WHO), the number of people with visual impairments is estimated to be more than 285 million worldwide and this number is growing every year [1]. Unfortunately, almost all visual disorders remain untreatable today and the quality of life of persons with low vision may be dramatically altered [2-3]. During the last two decades, different visual aids mainly based on optical devices have been developed to assist the low vision population. In the same time, image enhancement methods have also been introduced especially for helping visually impaired people to increase their perception of digital information. Such methods are for example used in broadcasting, in mobile visual aids using head-mounted devices or to improve reading rate [4-6].

Image enhancement approaches have proved their usefulness but they raise the question of the optimal choice of the method and its corresponding adjustment for a given application and a given pathology [7]. Usually such a problem is addressed subjectively by conducting experiments with patients. This type of evaluation is generally reliable but it is expensive, time consuming and complex to achieve. An alternative could be to use an objective quality metric. A large number of objective quality metrics are available in the literature but all existing metrics were developed to correlate with the visual perception of observers with normal or corrected to normal vision [8].

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This means that none of the existing quality metrics can be directly employed in the low vision context. Consequently we propose a framework which takes into account the perceptual particularities of people with visual impairments.

The paper is organized as follows: Section 2 provides a brief and general overview of the problem of image quality assessment. Section 3 presents the approach we propose in the context of low vision. Results of tests are summarized in Section 4 and Section 5 is dedicated to conclusion.

2 Image Quality Assessment

Image quality assessment is an important issue for a lot of image and video processing applications from acquisition to storage through transmission and display. It plays a key role not only for evaluating the effectiveness of algorithms but also for optimizing parameters in relation to the specificities of each problem to address.

Two families of approaches exist for image quality assessment: subjective and objective evaluations. Subjective evaluation requires a group of reference observers to obtain a Mean Opinion Score (MOS). The quality of the MOS highly depends on both the number of observers and the number of viewing sessions [9]. This presents the main drawback to be time consuming and expensive. Objective evaluation is based on a more or less complex mathematical model. A quality score is computed with the advantage of repeatability but with the disadvantage to have difficulties to accurately reflect the judgment given by human observers [10].

Nowadays more than 100 quality metrics are proposed in the literature [8] from the simplest and traditional indices such as the popular Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR) to the more sophisticated Perceptual Visual Quality Metrics (PVQM) [9]. This important number of existing methods is due to the fact that there is not a universal model that could be used in any context, quality metrics are application dependent. To tackle this problem, the wide range of PVQMs is most likely to provide a template that can be adapted to a given practical situation. For example, algorithms embodying the detection of artifacts such as blockiness and blurring effects are particularly appropriate for image quality assessment in image and video compression. In printing industry, most of metrics based on computational modules designed to process color information will be preferred [11].

PVQMs can be divided into two categories of approaches: the signal-driven algorithms and the vision-based models [9]. The first category mainly extracts and analyzes signal features such as statistical properties or structural information [12]. The second category integrates some characteristics of the human visual system such as the contrast sensitivity function (CSF), the properties of color channels or the luminance adaptation [13]. Both categories aim to quantify image quality according to "standard" human visual perception.

Considering only the global aim of image quality assessment, the general problem is the same for people with normal or corrected to normal vision and for the visually impaired. However, due to the differences in the capabilities of their respective visual system and according to the level of visual disorder, the evaluation of picture quality may significantly differ between the two populations of observers. This means that the existing quality metrics cannot be used in the situation of low vision since they were not designed for such a context [8]. The general framework is unchanged but new metrics have to be introduced to take into account the specificities of visual impairments.

As mentioned in the introduction, it has been shown that image enhancement techniques are useful for helping visually impaired people to increase their perception of digital information. Then the work presented in this paper is motivated by the evaluation of the quality of images that have been enhanced for people with low vision. The purpose of the quality metric we will describe in the following is to propose an alternative approach to subjective evaluations usually conducted with patients. Besides the problems of time and cost, subjective evaluations in the context of low vision suffer from the low number of patients ready for experiments. For example, Fine and Peli [6] collected data from 31 observers, Peli and Woods [7] from 25 observers, and Kim et al. [14] conducted experiments with 24 observers. Administrative issues between clinics and research laboratories can also require additional efforts and can significantly delay and make difficult the studies.

3 Proposed Framework for the Visually Impaired

3.1 Background

To determine what features are important for the visually impaired when evaluating the quality of enhanced images, the results of experiments conducted by various researches have been analyzed and exploited [4], [14-17]. During such experiments it has been commonly shown that patients perceive noise and artifacts when images are too strongly enhanced. Even if over-enhanced images facilitate the visual tasks of people with low vision, these kind of images are nevertheless rejected because they are considered too artificial and unpleasant [18]. Most patients prefer enhanced images to look natural i.e. to be as much structurally closer as possible to the original images. In addition, as vision disorders start with affecting high-frequency components, the visually impaired are not able to perceive frequencies higher than a given threshold, such a threshold being in direct relation to their visual acuity [2, 4]. This means that a quality metric used in the context of low vision should not take into account the visual information which could not be perceived. Thus, it might be useful to suppress from images frequencies that will not produce a visual perception for patients even after enhancement. Besides, color perception is not affected by most vision diseases. This makes color information in general and color contrasts more specifically a very significant feature as suggested by some studies [19].

Fig. 1 presents the general architecture of the quality measure we propose as an assistance to efficiently select an image enhancement algorithm for a visual aid dedicated to low vision people.

An objective quality score is obtained after three stages. The first stage simulates limitations introduced by visual impairments. The second stage corresponds to the computation of the quality attributes selected according to both the context of image enhancement for visual aids and the experimental results mentioned above. The third and last stage of the global process is a pooling step during which all the values derived from quality attributes are combined to provide the final objective score.

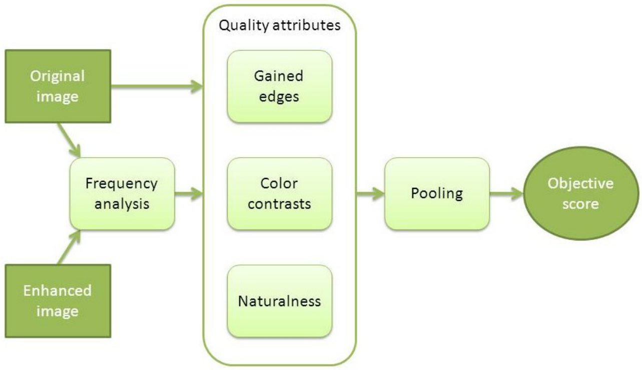

Fig. 1. General architecture of the quality measure we propose for low vision

3.2 Frequency Analysis

The first step of our model is derived from the analysis carried out by Schurink et al. [20]. Three categories of visual impairments have been considered: mild, moderate and severe. Generally speaking, the highest spatial frequency that can be perceived by observers decreases from one category to the next from mild to severe.

Log-cosine filters are used to simulate limitations introduced by visual impairments. Such filters allow to target the frequencies to eliminate and present the interesting advantage to have properties in correlation with the processing characteristics of the human visual system [21]. The general formulation of filters is given by:

$$C_i(f_x, f_y) = \begin{cases} 0.5[1 + \cos(\pi \log_2 r - \pi i)], & 2^{i-1} \le r \le 2^{i+1} \\ 0, & \text{elsewhere} \end{cases} \tag{1}$$

where i is the order of the filter and r the radial spatial frequency $r = \sqrt{{f_x}^2 + {f_y}^2}$.

Observers of the three categories of visual impairments mentioned above are not able to perceive frequencies higher than 8-10 cycles/degree [17]. These frequencies are consequently removed by using a 6th-order filter which corresponds to 64 cycles/image or 8 cycles/degree for an 8° image span [21]. Moreover, three other significant frequency bands are considered to take into account the perceptual limitations induced by the different categories of visual impairments. More precisely, a 5th-order filter is applied additionally to the 6th-order filter for mild visual impairment. Identically, a 4th-order filter is add to the 5th-order and 6th-order filters for moderate visual impairments and a 3rd-order filter is inserted in the frequency analysis stage for severe visual impairments.

3.3 Quality Attributes

Gained Edges. The function of the quality attribute *Gained Edges* (GE) is to compare edges of the original image with those of the enhanced image and to quantify if some gain in perception has been introduced. The output of this quality attribute is a value ranging from 0 to 1 which quantifies the ratio of edges that can be detected only in the enhanced image.

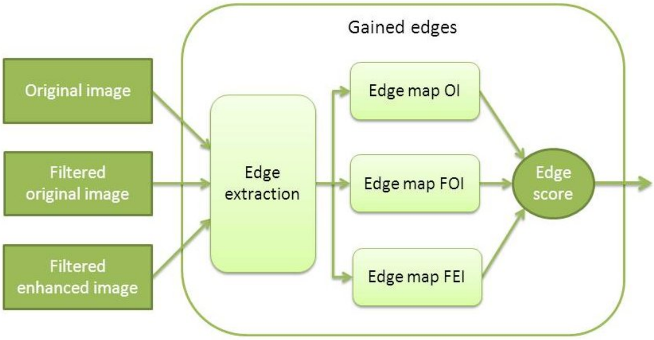

Fig. 2. Computation of the score provided by the quality attribute *Gained Edges* (GE)

As shown in Fig. 2, the quality attribute GE is fed by three input data: the original image and the filtered versions of the original image and the enhanced image obtained during the frequency analysis stage. An edge extraction algorithm is then used to compute three edge maps, one per input image. The Canny edge detector [22] has been chosen for its balanced trade-off between the accuracy of edge identification and the computational cost [23]. The output edge score is given by:

$$ES = \frac{K_1}{K_2} \quad (2)$$

where K_1 is the number of pixels present in both edge maps OI and FEI respectively derived from the original image and from the filtered enhanced image but that are not present in the edge map FOI derived from the filtered original image. K_2 is the number of pixels present in the original image.

Color Contrasts. The quality attribute *Color Contrasts* (CC) takes into account the local variations of chromatic information of scenes. Recent studies, as the one presented in [24], tend to prove that local contrasts are more correlate to human perception than global measures. Approaches considering contrasts at a global level mainly quantify maximum differences in brightness and/or chromaticity. They fail to reflect the spatial organization of visual information and they consequently neglect the influence of spatial properties of contrasts in human visual perception.

Local color contrasts are evaluated in IHLS (Improved Hue, Lightness, and Saturation) color space [25] on the basis of the color opponent theory in order to quantify if any chromatic gain is introduced during image enhancement. IHLS color space presents the double advantage of a simple and unambiguous color mapping from RGB color space and the independence of chromatic and achromatic channels. Thus, we can easily and efficiently use opponent colors to measure color contrasts.

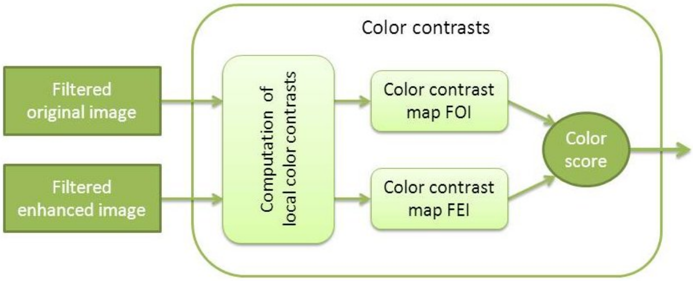

Fig. 3. Computation of the score provided by the quality attribute *Color contrasts* (CC)

As shown in Fig. 3, the quality attribute CC is fed by two input data: the filtered versions of the original image and of the enhanced image, both provided by the frequency analysis stage. Local color contrasts are computed with the algorithm proposed by Rizzi et al. [26]. The Euclidean distance between the coordinates of the colors of the neighborhood of each pixel of the two input images is calculated. Two color contrast maps are then derived from such a calculation. The output color score ranging from 0 to 1 is given by:

$$CS = \frac{K}{K_2} \tag{3}$$

where K is the number of pixels with increased color contrast and K_2 the number of pixels of the original image.

Naturalness. The naturalness attribute is based on the structural similarity (SSIM) index and the corresponding naturalness score (*NS*), ranging from 0 to 1, is computed with the relations proposed by Wang et al. [12]. The approach is derived from the assumption that the human visual system is adapted to extract structural information of scenes and that natural images are highly structured. By considering noise and artifacts as perceived changes in structural information, the SSIM index offers an efficient way to objectively evaluate naturalness defined by observers with low vision as a property of the enhanced image not to make appear visible degradations.

3.4 Pooling

The function of the last stage of the proposed framework is to combine the values given by the three distinct quality attributes in order to provide the final objective quality score ranging from 0 to 1. The computation is based on Minkowski pooling approach [27]:

$$QS = w_1 ES + w_2 CS + w_3 NS \quad (4)$$

where w_1, w_2 and w_3 are weights affected to quality attributes with $w_1 + w_2 + w_3 = 1$. Such a pooling approach presents both the advantage of simplicity and adaptability to the different visual deficiencies by simply changing the values of the weights.

4 Tests and Results

Due to the current absence of an appropriate database i.e. a database collecting the subjective evaluations given by visually impaired people, the evaluation of our framework is not obvious and cannot be conventionally realized by computing indicators as prediction accuracy and prediction monotonicity for example. To deal with such a problem, the consistency of the output scores has been studied by varying the adjustable parameters of the model. Table 1 summarizes the different combinations of weights used in the pooling stage for the study.

Table 1. Sets of weights used to study the consistency of the final quality score

Set number	w_1 (Edge Score)	w_2 (Color Score)	w_3 (Naturalness Score)
1	0.8	0.1	0.1
2	0.1	0.8	0.1
3	0.1	0.1	0.8
4	0.4	0.4	0.2
5	0.4	0.2	0.4
6	0.2	0.4	0.4
7	0.33	0.33	0.34

Quality scores have been calculated for 10 original images presenting various contents such as natural scenes, faces, buildings and for 6 enhanced versions of each of these images. The enhancement technique commonly used for helping visually impaired people to increase their perception of digital information has been selected. Such a technique is based on a spatial filtering [6] controlled by a contrast amplification coefficient referred as *enhancement level* (*EL*) and ranging from 1 to 7 in this paper. An enhancement level of 1 corresponds to the original image and the strength of the image enhancement increases with *EL* value (Fig. 4 shows an example).

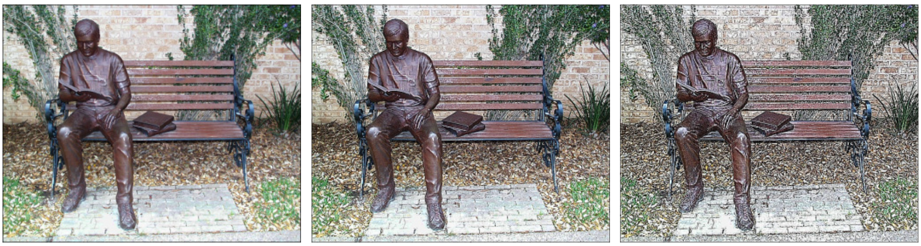

Fig. 4. From left to right: original image ($EL = 1$), processed image with $EL = 4$, $EL = 7$

4.1 Importance of Quality Attributes

In the pooling stage, an adjustable weight is affected to each quality attribute. As visual impairments vary with patients, quality assessment is not unique: some visually impaired observers prefer processed images to look natural with a moderate enhancement when others can disregard the naturalness if their perception of scenes is improved [18]. Thus, we studied how the pooling stage of our framework modifies the output quality score.

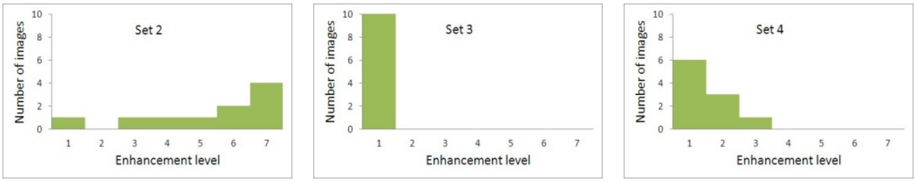

Fig. 5. Evolution of the highest objective quality score according to the selected set of weights

Histograms shown in Fig. 5 have been computed with the set of weights given in Table 1 and for the weakest filtering available in the frequency analysis stage. Histograms display the number of enhanced images obtaining the highest quality score for the different enhancement levels. Fig. 5 clearly shows that preferable level of enhancement changes according to the weights selected during pooling. We can notice that when the weight affected to the naturalness attribute is the highest, the lowest level of enhancement is preferable for all images. When the two attributes color contrasts and gained edges have higher importance, the result is spread among enhancement levels, especially for set 2. Enhancement levels greater than 5 obtain the highest quality score only if high weights are affected to color contrasts and/or to gained edges. A common property of all enhanced images is that naturalness is more and more deteriorated when the enhancement level increases (see Fig. 4). Then, if patients consider that the naturalness of enhanced images is not the most important parameter in the quality assessment, the quality score provided by the model is consistent with the subjective judgment.

4.2 Categories of Visual Impairments

An important feature of image quality assessment achieved by low vision people is that the judgment depends on the severity of their visual impairment. As explained in section 3.2, three categories of visual impairments have been considered: mild, moderate and severe. Then, it is important to test if the proposed framework is able to provide objective scores in relation with these categories of visual impairments.

Fig. 6 presents quality scores for mild (green curve) and moderate (red curve) visual impairments. Curves shown in Fig. 6 correspond to the image of Fig. 4 but results are common for the 10 images used for the study. The curves corresponding to moderate visual impairments are mostly above those in relation with mild visual impairments. This reflects that people with lowest visual acuity are less likely to be sensitive to artifacts introduced during the enhancement process. The shift of the peak value of the quality score for moderate visual impairment toward higher enhancement levels is in correlation with the need of stronger enhancement for this category of patients.

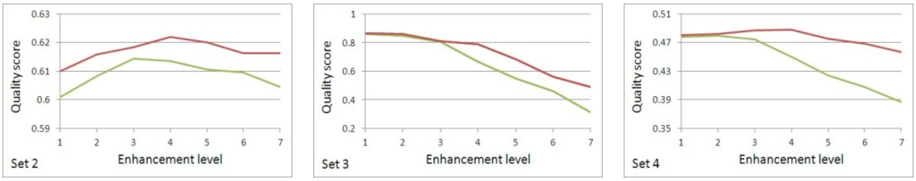

Fig. 6. Examples of quality curves for mild (green) and moderate (red) visual impairments

5 Conclusion

In this paper, a framework for objective image quality assessment in the context of low vision was proposed. Perceptual specificities of visually impaired people are taken into account to correlate the computed objective scores with the subjective judgments given when observing color enhanced images. The proposed framework combines three quality attributes specially selected for the relevancy of their properties to achieve this goal. These quality attributes have distinct and complementary functions: quantifying if a perceptual gain has been introduced for edges and colors during enhancement and evaluating if visible degradations appear.

With the absence of databases containing MOS obtained with low vision observers, our approach was tested by studying the evolution of the output score when modifying internal parameters. This study demonstrates the ability of the approach to adapt to different categories of visual disorders. Even if the framework described in this paper deserves further investigation, it is a first step in developing efficient computational methods to address the quality assessment issue for the visually impaired.

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