Enhancement of Human Visual Perception-Based Image Quality Analyzer for Assessment of Contrast Enhancement Methods

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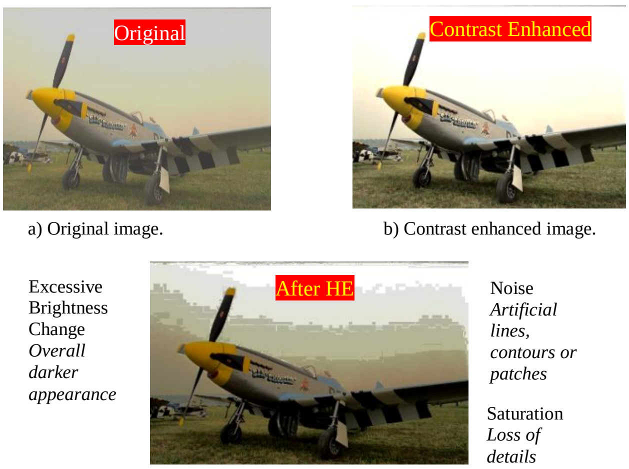
Abstract: *Prior to this work, Human Visual Perception (HVP) -based Image Quality Analyzer (IQA) has been proposed. The HVP-based IQA correlates with human judgment better than the existing IQAs which are commonly used for the assessment of contrast enhancement techniques. This paper highlights the shortcomings of the HVP-based IQA such as high computational complexity, excessive (six) threshold parameter tuning and high performance sensitivity to the change in the threshold parameters' value. In order to overcome the aforementioned problems, this paper proposes several enhancements such as replacement of local entropy with edge magnitude in sub-image texture analysis, down-sampling of image spatial resolution, removal of luminance masking and incorporation of famous Weber-Fechner Law on human perception. The enhanced HVP-based IQA requires far less computation (>189 times lesser) while still showing excellent correlation (Pearson Correlation Coefficient, PCC > 0.90, Root Mean Square Error, RMSE<0.3410) with human judgment. Besides, it requires fewer (two) threshold parameter tuning while maintaining consistent performance across wide range of threshold parameters' value, making it feasible for real-time video processing.*

Keywords: *Contrast enhancement, histogram equalization, image quality, noise, weber fechner.*

Received October 4, 2015; accepted March 30, 2016

1. Introduction

Contrast Enhancement (CE) is a very common image processing step to improve the quality of image. Figure 1-a and Figure 1-b show an original image and the image after CE respectively. Notice the enhanced image shows better visibility and is visually more pleasing. However, CE may cause annoying distortions. Figure 1-c shows an example of contrast enhanced image with annoying distortions like noise, saturation and excessive brightness change.



a) Original image.

b) Contrast enhanced image.

c) After HE.

Figure 1. Advantage and problems of contrast enhancement.

Histogram Equalization (HE) is one of the most commonly used CE techniques. Although adjustable HE-based CE techniques [4, 8, 10, 12, 15, 18, 22, 24] can avoid the problem of distortion by allowing user to regulate the degree of enhancement, fully automated CE technique [1, 2, 3, 6, 9, 16, 19, 23] is still the ideal solution. A recent study [5] showed that the automated techniques may still result in annoying distortions and this problem was likely due to the Image Quality Analyzer (IQA) used in the CE techniques evaluation. A new Human Visual Perception (HVP)-based IQA has been proposed to evaluate the annoyance of noise [2]. In the study, the HVP-based IQA outperformed other IQAs, including Absolute Mean Brightness Error (AMBE), Entropy and Multi-scale Structural Similarity Index (MSSIM). However, the HVP-based IQA suffers from the problems of high computational complexity which will further be explained in section 2.

Recently, there has been increasing interest to develop low complexity IQA for real-time application. A No-Reference (NR) IQA called Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) was proposed by [13] and it was 70 and 149 times faster than the two most prominent NR-IQAs called Distortion Identification-based Image Verity and Integrity Evaluation (DIIVINE) and BLind Image Integrity Notator using DCT-Statistics (BLIINDS)-II respectively. Liu *et al.* [11] proposed another No-

Reference Image Quality Assessment Algorithms (NR-IQA) called Oriented Gradients Image Quality Assessment (OG-IQA) which was faster and more accurate than BRISQUE. A new Video Quality Assessment algorithm (VQA) was proposed by [14]. The new VQA was 68 times faster than a prominent Video Quality Assessment Algorithm (VQA) called MOtion based Video Integrity Evaluation index (MOVIE).

This paper aims to propose an enhanced HVP-based IQA with lower computational complexity, fewer parameter settings and lower performance sensitivity to parameter change. The rest of this paper is organized as follows: Section 2 presents the analysis and highlights the shortcomings of the HVP-based IQA. Section 3 presents the enhancement strategies and the detail algorithm of the enhanced HVP-based IQA together with algorithm analysis. Section 4 presents the discussion of the results of the experiment and Section 5 presents the concluding remarks.

2. Analysis of HVP-based IQA

The computational complexity in terms of the number of clock cycle for each process of the HVP-based IQA is as listed in Table 1. In summary, the computational complexity is 1517 clock cycles per pixel. For common digital TV standard such as DVD National Television System Committee (NTSC) with resolution of 720x480 pixels per frame and 23.97 frames per second, the required computation power is 720×480×1517×23.97=11.7 Giga clock cycles per second. Such demanding computation power would impose a great challenge to real-time video processing.

Table 1. Number of clock cycle for each process of the HVP-based IQA.

Eq.in [2]	**Process**	**Computation Per Pixel Location**				
		Addition, Subtraction, Shift, Logical, Relation *(1 clock cycle)*	**Multiplication, Division** *(3 clock cycles)*	**Log** *(10 clock cycles**)*	**Square Root** *(10 clock cycles**)*	**Total clock cycles**
3	Gray conversion	2	3			11
4	Edge Detection	1	2		1	32
5		6				
6		6				
7						
8		3				
9						
10	Local Luminance	8	1			11
11	Noise classification	5				5
12	Local Entropy	80	81*	81*		1457
13			81			
14		81				
15						
16	Aggregation	1				1
	Total	193×1	168×3	81×10	1×10	1517

*Based on worst case scenario where all pixels in sub image are having different gray level so there are 81 non-zero histogram bins.

**Based on estimation for simplicity

Figure 2 shows the 3D graph of the HVP-based IQA's performance vs. threshold parameter values (T_o and T_d). It is observed that the value of correlation coefficient drops drastically as the value of T_o is tuned away from 0.002. Figure 3 shows the graph of the HVP-based IQA's performance vs. threshold parameter values (H_T). Notice that the correlation decreases quickly as H_T is tuned away from 2. Both Figures 2 and 3 reveal the IQA's shortcoming of being highly sensitive to the change of the threshold parameters' value. Besides, the HVP-based IQA also has the disadvantage of having excessive (six) threshold parameters which complicate the tuning process.

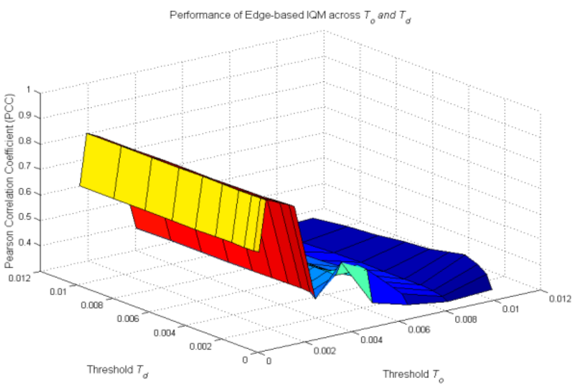


Figure 2. 3D graph of the HVP-based IQA's performance vs. threshold parameter values (T_o and T_d).

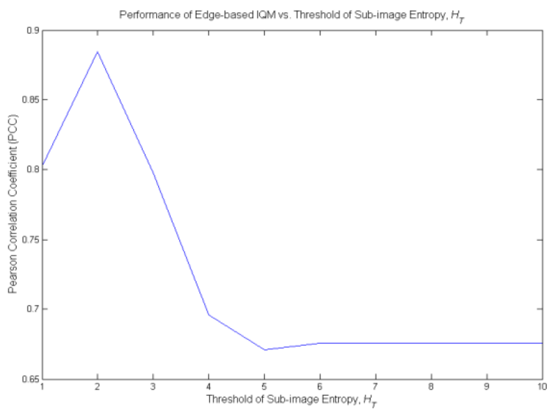


Figure 3. Graph of HVP-based IQA's performance vs. Threshold parameter values (H_T).

3. The Enhanced HVP-based IQA

3.1. Strategies to Enhance HVP-Based IQA

This paper proposes two enhancements to the HVP-based IQA. The first enhancement is to reduce the algorithm complexity while the second enhancement is to reduce the number of threshold parameters.

- *Reduction of algorithm complexity*: There are two strategies to reduce the algorithm complexity. The first strategy is to identify and simplify the process which requires massive computation. It is observed from Table 1 that local entropy demand the most intensive computation. Therefore, it is desirable to replace it with a measure which requires less computation. Local entropy serves to reflect sub-image's texture (smoothness) which is basically changes in brightness. This paper proposes to replace entropy with edge magnitude which may serve the same purpose where smooth texture tends to have low edge magnitude. The advantage of using edge magnitude is that it does not require additional computation because it has been pre-computed in the process of Edge Detection (refer Equations (4, 5, 6, and 7) in [2]).

The second strategy is to perform down-sampling to reduce image spatial resolution. Although it might reduce the prediction accuracy of IQA, it can effectively reduce computational complexity, especially for algorithm with sliding window operation. By reducing the spatial resolution both horizontally and vertically to $1/N$ of the original resolution, the number of sliding window operation can be practically reduced to $1/N^2$. The window size would also be reduced proportionally. Consequently, the number of computation for each sliding window operation would be reduced to $1/N^2$. Therefore, the overall number of computation can be reduced to as low as $1/N^4$. However, the process of down-sampling itself requires some computation. Thus the actual complexity reduction ratio is also dependent on the complexity of the sliding window operation as shown in Equation (1).

$$\text{Reduction Ratio} = \frac{\text{Original no. of computaton}}{\text{Reduced no. of computation}} = \frac{WHS}{\frac{WHS}{NNN^2}+Q} = \frac{WHS}{\frac{WHS}{N^4}+Q} = \frac{WHS}{WHS+QN^4}N^4 \tag{1}$$

where,
W: image width
H: image height
S: no of computations for a sliding window operation
N: down-sampling factor
Q: no of computation for down-sampling
Since the number of computation for down-sampling, Q tends to be proportional to image size, let $Q=RWH$ where R is a constant
Then, Equation (1) would become

$$\frac{WHS}{WHS+RWHN^4}N^4 = \frac{S}{S+RN^4}N^4 \tag{2}$$

Equation (2) shows that if $S \gg RN^4$, then the reduction ratio would be closed to N^4. This is usually the case in reality. In the case of Human Visual Perception (HVP)-based IQA,$R \approx 1$, $N \approx 2$ and S=1514, so the reduction ratio is approximately $2^{4=}16$.

- *Reduction of threshold parameters*: The threshold parameters are reduced in three ways. The threshold parameters H_T, and n are no longer required as local entropy has been replaced with edge magnitude as mentioned above. T_o and T_d used to detect noise are replaced with a new threshold parameter by incorporating the famous Weber-Fechner Law of Perception. The details formulation of the proposed IQA is described in the next section. The threshold parameters L_{low} and L_{high} used in luminance masking are no longer required as luminance masking is removed from the IQA. This is following the observation that the prediction accuracy of HVP-based IQA would not be affected significantly without luminance masking.

3.2. Formulation of Enhanced HVP-based IQA

This paper proposes to predict the presence of noise by detecting excessive contrast gain in sub-image with smooth texture [7]. The ratio of post-enhancement sub-image's edge magnitude to pre-enhancement sub-image's edge magnitude is used to gauge the contrast gain. High ratio indicates high contrast gain. Sub-image with unusual high contrast gain ratio, i.e. low edge-magnitude (smooth texture) before contrast enhancement and high post-enhancement edge-magnitude tends to show visible noise.

This paper proposes to estimate the IQA score as a function of the "noise annoyance" of such sub-images in which noise are likely to be visible and annoying. In principle, high contrast gain contributes to higher "noise annoyance". Since "noise annoyance" is related to human perception, this paper proposes to incorporate the famous Weber-Fechner law to account for different level of "noise annoyance". Weber-Fechner law combines two different laws of human perception:

1. *Weber's law* -the just-noticeable difference between two stimuli is proportional to the magnitude of the stimuli
2. *Fechner's law*-subjective sensation is proportional to the logarithm of the stimulus intensity.

Weber-Fechner law outlines the relationship between stimulus, S and perception, p as in Equation (3):

$$p = k \ln \frac{S}{S_0} \tag{3}$$

Where, S_o is the threshold of stimulus below which there is no perception (p=0) and k is a scaling constant [17].
The following are steps to compute the quality score:

Step 1: Compute EM_d^2 and EM_o^2- the square of edge magnitude (refer Equation (4) in [2]) of pre and post-enhancement sub-image respectively.
Step 2: Compute contrast gain ratio, $Q(r,c)$ as defined in Equation(4):

$$Q(r,c) = \frac{EM_d^2(r,c)+\varepsilon}{EM_o^2(r,c)+\varepsilon} \tag{4}$$

Where ε is a small constant much smaller than the values of $EM^2(r,c)$. It is used to prevent zero division. In the implementation, ε is set to 10^{-15}

Step 3: Compute the "noise annoyance" according to their respective contrast gain ratio, $Q(r,c)$ based on Weber-Fechner Equation as defined in (5):

$$I_n(r,c) = \begin{cases} \ln \dfrac{Q(r,c)}{Q_o} & \text{if } Q(r,c) \geq Q_0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Where

Q_0: the threshold contrast gain which can cause "noise annoyance"

Step 4: Compute the IQA rating, R as the sum of $I_n(r,c)$, normalized by the image size as defined in Equation (6):

$$R = \frac{1}{HW} \sum_{r=1}^{H-2} \sum_{c=1}^{W-2} I_n(r,c) \tag{6}$$

Where:

H: image height

W: image width

3.3. Analysis of Algorithm

a) *Threshold Parameter Tunings*

In principle, the optimum value of sub-image size, n is dependent closely on the image size. Larger image size would require large sub-image size. Hence, the ratio of sub-image size to image size should be kept within a reasonable range. This paper proposes to maintain the ratio by reducing image size (down-sampling) for

1. It is more flexible compared to changing sub-image size which is constraint to be an odd num ≥ 3 and more importantly.
2. It could effectively reduce the overall computational complexity.

The down-sampling factor is set according to (7) to so that the maximum dimension of down-sampled image would be equal to *sz*. The complexity to compute sub-image's variance would increase exponentially following the size of sub-image, n. Therefore, it is desirable to minimize the value of n to 3.

$$\frac{\text{sz}}{\max\{\text{original height, original width}\}} \tag{7}$$

Essentially, the proposed IQA requires only two parameter tunings-the down-sampled image size and threshold contrast gain, (sz, Q_0). It is desirable that the IQA's performance is not too sensitive to the change in the parameters' value and to different sets of input images. A study has been conducted to evaluate the consistency of the IQA's performance. The proposed IQA showed consistent performance across wide range of the parameters' value and different sets of test images. The detail results are reported in section 4.2.

b) *Computational complexity*

The computational complexity in terms of number of clock cycles for each process of the proposed fast IQA is as listed in Table 2. In summary, the computational complexity is 90 clock cycles per pixel. The speedup ratio compared to the HVP-based IQA is 1517 : 50 or 30.34 : 1. The computational complexity would be reduced even more if taking into account the process of down sampling; for common digital TV standard such as DVD (NTSC) with resolution of 720×480 pixels per frame, the down-sampling ratio with sz = 288 would be $1 \div (288 \div 720)^2 : 1$ or 6.25 : 1. This would result in a remarkable overall reduction ratio of 30.34×6.25 : 1 or 189.63 : 1.

Table 2. Number of clock cycle for each process of the proposed IQA.

Process	Computation Per Pixel Location				
	Addition, Subtraction, Shift, Logical, Relation ***(1 clock cycle)***	**Multiplication, Division** ***(3 clock cycles)***	**Log** ***(10 clock cycles**)***	**Square Root** ***(10 clock cycles**)***	**Total clock cycles**
Gray conversion	2	3			11
Edge Detection – STEP 1	1	2			19
	6				
	6				
Contrast Gain Ratio-Equation. 4	2	1			5
Noise Annoyance-Equation. 5	1	1*	1*		14
IQA Score-Equation. 6	1				1
Total	19×1	7×3	1×10	-	50

*Assuming worst case scenario where all sub-images are having $Q(r,c) \geq Q_0$ although the actual number tends to be very small in average (<0.1%).

**Based on estimation for simplicity.

4. Evaluation Results

4.1. Prediction of Subjective Quality

For fair comparison, the test images and procedures used for the evaluation is the same as those used to evaluate the HVP-based IQA [2]. According to the recommendations in "VQEG Final Report of FR-TV Phase 2 Validation Test" by Video Quality Experts Group (VQEG) [21], the performance of an IQA can be quantitatively evaluated with respect to its ability to predict subjective quality rating in the following three aspects

1. *Prediction Accuracy*: the ability to predict the subjective quality score with low error. The metrics used were

1. Pearson Correlation Coefficient (PCC).
2. Root Mean Squared Error (RMSE).

2. *Prediction Monotonicity*: the degree to which the model's prediction agrees with the relative magnitudes of the subjective quality rating. The metric used was Spearman Rank Order Correlation Coefficient (SROCC).
3. *Prediction Consistency*: the degree to which the model maintains prediction accuracy over different types of images and not to fail excessively for a subset of images. The metric used were Outlier ratio (OR - ratio of outlier to total scores). Outlier score is score outside an interval of two times the standard deviation about the Mean Opinion Score (MOS).

The evaluation was done using MOS after non-linear regression using a five-parameter logistic function (a logistic function with an added linear term, constrained to be monotonic) [20] as defined in Equation (8)

$$R(x) = b_1\left(\frac{1}{2} - \frac{1}{1+e^{b_2(x-b_3)}}\right) + b_4 x + b_5 \quad (8)$$

This nonlinearity was applied to the MOS or its logarithm, which gave a better fit for all data.

The results in Table 4 show that the proposed fast IQA consistently outperforms HVP-based IQA in terms of Pearson CC and Root Mean Squared Error (RMSE). The fast IQA is comparable to HVP-based IQA in predicting subjective quality rating but with far less of computation.

Table 4. The results of Pearson CC, RMSE, SROCC and OR.

	PCC	RMSE	SROCC	OR
HVP-based IQA *(without scale masking)*	0.8687	0.3815	0.8990	0
Proposed IQA (sz=288, Q_0=10)	*0.9019*	*0.3405*	*0.8824*	*0*

4.2. Performance Consistency

Figures 4 and 5 show 3D graph of the proposed IQA's performance in terms of PCC and SROCC respectively for each pair of parameter, (sz, Q_0) where $sz \in \{128,160,192,..,512\}$and $Q_o \in \{128,160,192,..,512\}$. Notice that the proposed IQA demonstrates good correlation (PCC/SROCC $\geq$ 0.76) across majority ($\geq$ 95%) of parameter values in the study. The results indicate that the performance is consistent across wide range of threshold parameters' value.

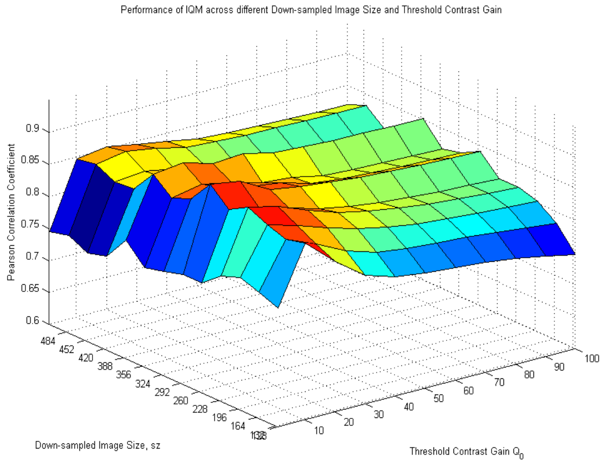


Figure 4. 3D Graph of the proposed IQA's Performance (PCC) vs. Parameters' Values (sz, Q_o).

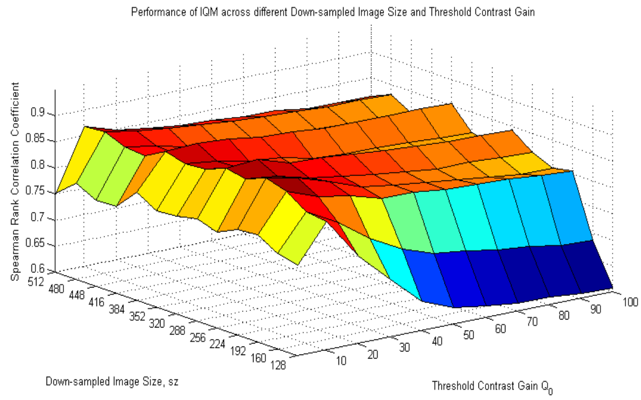


Figure 5. 3D Graph of the proposed IQA's Performance (SROCC) vs. Parameters' Values (sz, Q_o).

5. Conclusions

This paper highlights the disadvantages of the IQA such as high computational complexity, excessive threshold parameter tunings and high performance sensitivity to the change in threshold parameter value. Several enhancements have been proposed to overcome the aforementioned problems. Among the strategies include replacement of local entropy with edge magnitude in sub-image texture analysis, down-sampling of image spatial resolution, removal of luminance masking and incorporation of Weber-Fechner Law on human perception. The evaluation results showed that the enhanced HVP-based IQA could perform 189 times much faster than the HVP-based IQA while maintaining excellent correlation to human judgment. Besides, it requires far fewer threshold parameter tunings and demonstrates consistent performance across wide range of threshold parameters' value, making it feasible for real-time video processing

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