Image Quality Assessment Using Self-adaptable Bacterial Foraging Optimization Algorithm

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Abstract - There are a lot of successful image quality metrics in order to assess its perceptual quality that rely on the structural information in an image. It is a challenging task to extract the structural information that is perceptually meaningful to the visual system. In this paper we present new approach to the objective image quality assessment based on self-adaptable bacterial foraging optimization (SABFO). SABFO algorithm was applied on difference image (difference between original and distorted image). SA-BFO adjusted the run-length unit parameter dynamically during evolution to balance the exploration/exploitation trade-off. Experimental results demonstrate that the proposed technique has high correlation with results of subjective test and low computational time important for real-time applications. A marked improvement in performance over other image quality metrics was shown by application of SA-BFO on several benchmark functions shows**.**

Keywords - *Image Quality Assessment (IQA), Self-adaptable Bacterial Foraging Optimization Algorithm (SA-BFOA), Particle swarm optimization (PSO), Mean Opinion Score (MSO).*

I. INTRODUCTION

Visual image quality assessment method plays a vital role in various image processing applications. Image quality measures are mainly of two types. First is Subjective image quality assessment measure in which, with the help of human observers, Mean Opinion Score (MOS) is estimated. Second is Objective image quality assessment measure in which the quality of an image is estimated using mathematical expressions. However, there are two reasons due to which later technique is proved to be better than the previous one. First, due to its low computational complexity, they are easy to assess [1]. Second, they are independent of human visual perception. Due to involvement of number of observers and their numbers of corresponding results, Subjective methods are inconvenient and costlier to use, although viewing conditions play important role in human perception of visual image quality. The two extensively used objective quality measures among objective visual assessment approaches are Mean-square error (MSE) and Peak Signal-to-noise ratio (PSNR). But, they do not correlate well with human perception [2]. Various new quality methods have been suggested as replacements during the last few decades, for example SSIM [10], UQI [8], MSSIM [9] etc. But none of them outperforms the other.

The basic idea is to estimate the quality of an image using self-adaptable bacterial foraging optimization algorithm. First, we collect a large number of test images. Each image has a score labelled by human observers. Second, we evaluate scores associated with different metrics for each image. Then, we calculate the SABFO score to estimate image quality.

II. PREVIOUS WORK

Y. Kang-long, *et al.*, presented an improved reduced-reference image quality assessment (RRIQA) method that was based on the structural similarity image metric (SSIM) and scale invariant feature transform (SIFT). The method was applicable to super-resolution image, and more than one reference image was considered. Super-resolution (SR) was the technique that constructs high-resolution (HR) images from low-resolution (LR) images [3]. S. A. Golestaneh, *et al.*, presented a no-reference quality assessment algorithm for JPEG compressed images (NJQA), in which quality was estimated by first counting number of zero-valued DCT coefficients within each block, and then quality relevance map was used to weight those counts. The quality relevance map for an image was a map that indicated which blocks had naturally uniform/non-uniform vs. which blocks had been made uniform/non-uniform via JPEG compression [4].

E. Dumic, *et al.*, presented new approach to the objective image quality evaluation based on discrete wavelet transform (DWT) and particle swarm optimization (PSO). DWT was applied on image difference that is decomposed into approximation and detail sub-bands and DWT coefficients were computed. The coefficients were used to compute new image quality measure (IQM) that is defined as perceptual weighted difference between coefficients of original and degraded image. Weighting factors for wavelet sub-bands had been experimentally determined using PSO optimization algorithm [5]. Y. Wang, *et al.*, proposed a new approach, structural information based image quality metric for IQA that evaluated image distortion by computing the distance of Histograms of Oriented Gradients (HOG) descriptors. This metric was based on the fact that HVS is quite sensitive to image local orientation features. The proposed HOG IQA metric has low computing complexity and outperformed the conventional quality metrics such as PSNR, and SSIM. It was also comparable with VIF metric [6]. H. Chen, *et al.*, analyzed how the run-length unit parameter controls the exploration and exploitation ability of BFO, and then presents a variation on the original BFO algorithm, called the Self-adaptive Bacterial Foraging Optimization (SA-BFO), employing the adaptive search strategy to significantly improve the performance of the original algorithm. This is achieved by enabling SA-BFO to adjust the run-length unit parameter dynamically during evolution to balance the exploration/exploitation trade off. Application of SA-BFO on several benchmark functions had shown a marked improvement in performance over the original BFO [7].

III. EXPERIMENTAL STUDY

During last few years, the number of objective metrics has been developed. We use five metrics listed in Table 1. We observe that different metrics perform differently for different distortion types.

A. *Metrics Used*

Five metrics are used, given in table 1.

TABLE 1: FIVE METRICS USED

Metric Index	m1	m2	m3	m4	m5
Metric Name	SNR	PSNR	SSIM	UQI	PSO

B. *TID2013 Database (Test Database)*

Furthermore, in order to analyze the full reference visual image quality assessment metrics, TID2013 (Tampere Image Database2013) is used. TID2013 gives the corresponding results of the given metric to the mean human visual perception in approximation.

There are 25 reference images, 24 types of distortions for each reference image, and 5 unlike levels for each type of distortion in TID2013 [11]. 3000 distorted images are enclosed in the entire database. Reference images are attained by cropping from Kodak Lossless True Color image suite and kept them in database in Bitmap setup without any compression. File name of each image specify a number of the original image, a number of distortion's type and a number of distortion's level: "iAA_BB_C.bmp". 971 experiments were passed out by 971 observers from five countries: Finland, France, Italy, Ukraine and USA to attain MOS which ranges from 0 to 1 with MSE 0.018 for each score. About 524340 assessments of visual quality of distorted images or 1048680 assessments of relative visual quality in image sets were done. Distortion types in TID2013 are listed in table 2 [11].

TABLE II: TYPES OF DISTORTION IN TID2013

S. No.	Type of Distortion
1	Additive Gaussian noise
2	Different additive noise in color components
3	Spatially correlated noise
4	Masked noise
5	High frequency noise
6	Impulse noise
7	Quantization noise
8	Gaussian blur
9	Image denoising
10	JPEG compression
11	JPEG2000 compression
12	JPEG transmission errors
13	JPEG2000 transmission errors
14	Non eccentricity pattern noise
15	Local block-wise distortions of different intensity
16	Mean shift (intensity shift)
17	Contrast change
18	Change of color saturation
19	Multiplicative Gaussian noise
20	Comfort noise
21	Lossy compression of noisy images
22	Image color quantization with dither
23	Chromatic aberrations
24	Sparse sampling and reconstruction

C. *Benchmark Functions*

Four functions are contained as the set of benchmark functions that are commonly used in evolutionary computation literature to show solution quality and convergence rate [7]. The formulas of these functions are listed below.

1. *Sphere function*

$$f_1(x) = \sum_{i=1}^{n} x_i^2 \qquad x \in [-5.12, 5.12]^D \qquad (1)$$

2. *Rosenbrock function*

$$f_2(x) = \sum_{i=1}^{n} 100 * (x_{i+1} - x_i^2)^2 + (1 - x_i)^2 \qquad x \in [-3,3]^D \qquad (2)$$

3. *Rastrigin function*

$$f_3(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10) \qquad x \in [-5.12,5.12]^D \qquad (3)$$

4. *Griewank function*

$$f_4^x = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \qquad x \in [-600,600]^D \qquad (4)$$

TABLE 3: PARAMETERS OF SABFO

Function	S	$C_{initial}$	$\varepsilon_{initial}$	K_u	α	β
Sphere	1	0.1	100	20	10	10
Rosenbrock	1	0.1	100	20	10	10
Rastrigin	1	0.1	100	20	10	10
Griewank	1	0.1	100	20	10	10

Table 3 indicates the parameters set for SABFO. The standard PSO algorithm is used having default parameters [7].

D. SABFOA

First of all, we select the reference image and query image from TID2013. After that, using MATLAB algorithm, we evaluate the scores of existing metrics. Then, using SABFOA, new score is set. Based on that score fitness function is calculated as given below

$$Fitness\ function = \sum\sum(x-y) \qquad (5)$$

Where, x is the reference image, and y is the query image; x and y both are 2-D images.

$$Final\ Score = \frac{1}{d_{m1}d_{m2}}\sum_{i=1}^{2}\sum_{j=1}^{4}W_{ij}E_{ij} \qquad (6)$$

Where, d_{m1} is the width of reference image, d_{m2} is the height of the reference image, i is the sub-band level, j is the sub-band orientation, E_{ij} is the error distance for each sub-band, and W_{ij} is the weighting factor. Hence, $Final\ Score$ gives the quality of an image i.e. more the score better is the quality.

IV. RESULTS

The graphic user interface (GUI) developed using Matlab 2014a. In order to calculate the image quality, metrics– PSO, SNR, PSNR, SSIM, and UQI are used. Using SABFO, the image quality score per query image is calculated and the obtained results are shown in the text boxes adjacent to "Query Image #1" and "Query Image #2" labels, respectively, as shown in fig. 1.

We have considered 16th reference image as a test case from the TID2013 database as the original reference image as shown in fig. 1. Query Image #1 is the image corrupted by 1st type of distortion with 1st distortion level having MOS of 5.61538. Query Image #2 is the image corrupted with 6th type of distortion with 5th distortion level having MOS of 3.58974. Thus, Query Image #1 is of better quality than Query Image #2. In this case we can say that SABFO gives accurate scores than SNR, PSNR, SSIM and UQI.

Fig. 2 shows the test case 2 in which Query Image #1 is image distorted with 24th type of distortion with 3rd distortion level having MOS of. Query Image #2 is the image distorted with 10th type of distortion with 5th distortion level having MOS of. Thus, Query Image #1 is of better quality than Query Image #2. In this case we can say that SBFO ties with MOS whereas PSO fails in this case.

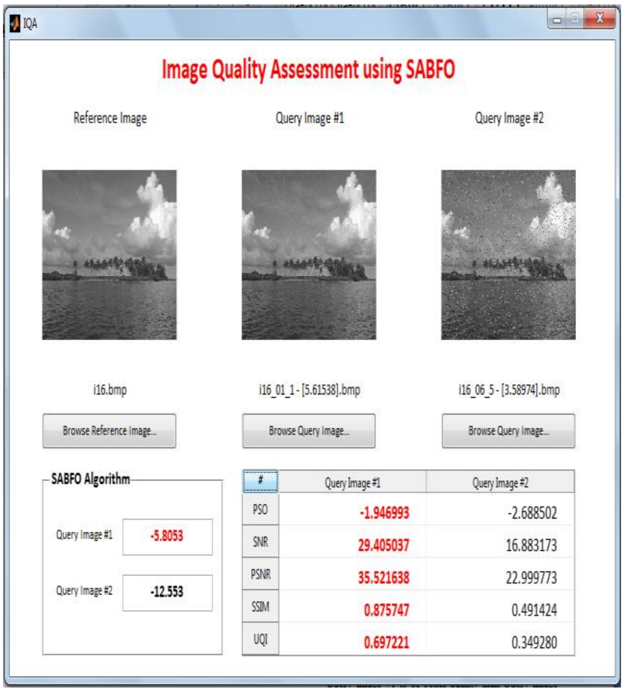

Fig.1: Test Case 1`

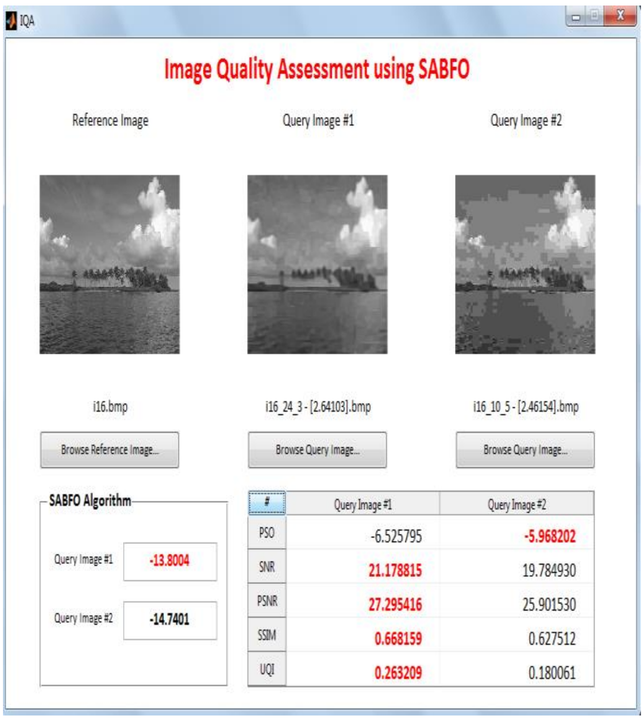

Fig. 2: Test Case 2

In order to calculate each of the objective measures, average time is required that is given in table 4.

TABLE 4: AVERAGE TIME REQUIRED FOR EACH IMAGE QUALITY ASSESSMENT

Measure	Total Time (in secs)	Average Time (in secs)
SABFO	4.3125297293	0.0359377477
PSO	5.3655400539	0.0447128338
SNR	0.7853965143	0.0065449710
PSNR	0.2835978071	0.0023633151
SSIM	6.8045098422	0.0567042487
UQI	9.3399918074	0.0778332651

It is clear from the above results that computational time of SABFO is less than PSO, SSIM and UQI i.e. $Time_{SABFOA} < Time_{PSO} < Time_{SSIM} < Time_{UQI}$.

V. CONCLUSION

In this paper, we presented a technique to estimate the quality of an image using Self-adaptable Bacterial Foraging Optimization algorithm. The properties of human visual system are taken into account to measure the quality of an image quality. This technique provides better results than some other quality measures. It also works well with image databases like TID2013. For evaluation, the proposed measure is considered as a good starting point and in real-time applications; it provides fair comparison of different types of image degradations.

VI. REFERENCES

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