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Image Quality Assessment using PSO-GSA Optimization Algorithm

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Abstract

In this paper, we present new method to the objective image quality evaluation based on discrete wavelet transform (DWT) and Particle Swarm Optimization and Gravitational Search algorithms (PSO-GSA). DWT is applied on the difference between the original and degraded image, which is decomposed into approximation and detail sub-bands. DWT coefficients are computed using Haar wavelet filter banks. The coefficients are used to compute new image quality measure that is defined as perceptual weighted difference between coefficients of original and degraded image. Weighting factors for wavelet sub-bands have been experimentally determined using PSO-GSA algorithm to achieve the best possible correlation with results of subjective (perceptual) image quality evaluation. Test case results demonstrate that the proposed technique has high correlation with results of subjective test and low computational time important for real-time applications. The test cases also show that this image quality assessment method has a better results than traditional method and it can accurately reflect the image visual perception of the human eye.

Keywords:*-Discrete Wavelet Transform, Image Quality Measure, MSE, MSSIM, PSNR, SSIM, UQI, VSNR,*

1. Introduction

Discrete wavelet transform (DWT) can be used in various image processing applications, such as image compression and coding [1]. In this paper we examine how DWT can be used in the image quality evaluation, which has become crucial for the most image processing applications. Quality of image can be assessed using dissimilar measures. The best way to do this is by making visual experiment, under controlled situations, in which human observer's grade which image provides enhanced quality. Such experiments are time consuming and costly. Much easier approach is to use some objective measure that evaluates the numerical error between the original images and tested one. In real world, there is no perfect way for objective assessment of image quality [2]. However, there is no current standard and objective definition of image quality.

2. Simulation Database

For performance evaluation, we chose the Tampere Image Database (TID2013) [3]. TID2013 is intended for evaluation of full-reference image visual quality assessment metrics. TID2013 allows estimating how a given metric corresponds to mean human perception.

The TID2013 contains 25 reference images and 3000 distorted images (25 reference images × 24 types of distortions × 5 levels of distortions). All images are saved in database in Bitmap format without any compression. File names are organized in such a manner that they indicate a number of the reference image, then a number of distortion's type, and, finally, a number of distortion's level: "iXX_YY_Z.bmp".For example, the name "i03_08_4.bmp" means the 3-rd reference image corrupted by the 8-th type of distortions with the 4-th level of this distortion. Similarly, the name "i12_10_1.bmp" means that this is the 12-th reference image corrupted by the 10-th type of distortion with the first level. "i17.bmp" means that this is non-distorted 17-th reference image.The Mean Opinion Scores (MOS) for this database were [4]obtained from the results of 971 experiments carried out by observers from five countries: Finland, France, Italy, Ukraine and USA (116 experiments have been carried out in Finland, 72 in France, 80 in Italy, 602 in Ukraine, and 101 in USA). Higher value of MOS (0 - minimal, 9 - maximal) corresponds to higher visual quality of the image.

Some of the existing objective measures described in previous section did not take into account HVS in the sense that eye will see and grade image quality according to the type of an error, as well as location of an error in sub-band space. Because of that, our method calculates image quality using wavelet decomposition and grades quality depending on the wavelet sub-band in which error occurs. Experiments on image databases have shown that

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different types of image degradation produce different error distributions in wavelet sub-bands. For example, for JPEG and JPEG2000 compressed images errors will be placed in the higher wavelet sub-bands (HH sub-band, level 2 and higher) while images with Gblur and Fastfading degradations will also have errors in lower sub-bands. White noise has equally distributed errors in all sub-bands.

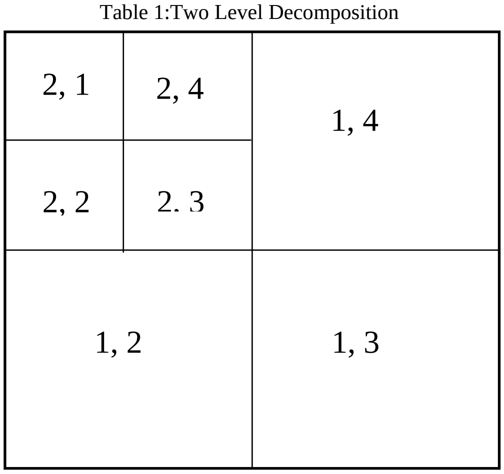
3. Discrete Wavelet Transform

In our research work error image of luminance component (difference between original and degraded image) is firstly transformed using DWT. [5] Discrete wavelet filter is used because it gives best results on both image databases, has even lengths and linear phase,after decomposing difference image into 2 leveldecomposition, error distance in each wave

$$E = \sum_i \sum_j |e_{i,j}| \quad (1)$$

In Eq. (1)$e_{i,j}$, are coefficients from difference image in the same sub-band. Weighting factors for level 2 decomposition have been experimentally [6]determined using PSOGSA optimization algorithm [7]and subjective scores from TID2013 database. They are presented in Table 1.

Table 1:Two Level Decomposition



Final measure IQM is then calculated as:

$$\text{Fitness Funtion} = @(x, y)\ \ \text{sum}(\text{sum}(x - y))$$

We used (normalization)so that final IQM measure won't have high values and they don't influence on the correlation results very much. Fromabove Table, it can be seen that all sub-bands have to be included inIQM measure, some have to be calculated using negativeweighting factor (experimentally they give better results). Also,[8]higher decomposition levels made our measure overfitted toTID2013 database so it gave somewhat worse results on oursubjective database (and only slightly better results on TID2013database).

Weighting factors for 2 level decomposition have been experimentally determined using PSOGSA algorithm which gives the best possible correlation results. They are presented in Table 2.

Table 2:Weighting Factors

Orientation (θ)	**Level (λ)**	
	1	**2**
1	-	1
2	-0.211	-0.921
3	-4.6	1.7
4	-0.211	-0.921

The Weighting factors, W_{lo} are multiplied with the corresponding Error Distances, E_{lo} obtained from the previous block, and the resultant variables are transferred to the final block for quality score assessment.

The Fitness Function Range, $\{rMin, rMax\}$ which is specified according to the subband level whose weighting factor we need to find. The corresponding range values, $\{rMin, rMax\}$, per subband level can be found experimentally by finding the minimum and the maximum difference between the pixels of the current subband of the original and all the degraded images present in the database used for simulation purpose.

4. PSO-GSA algorithm

4.1 Particle Swarm Optimization

PSO-GSA algorithm is used for the image quality assessment, In the PSO the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories [9] of a set of particles according to a swarm-like set of rules. The position of each particle is used to compute the value of the function to be optimized. Consequently every position is a particular solution of the optimization problem. Individual particles traverse the problem hyper-space and are attracted by both the position of their best past performance and the position of the global best performance of the whole swarm.

4.2 Gravitational Search Algorithm (GSA)

In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial [9] masses are determined using a fitness function. In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, we expect that masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space.

5. Final Score

The Final score is calculated using the following formulae,

$$\text{Image Quality Score} = \frac{1}{dim_1 * dim_2} \sum_l \sum_o W_{lo} * E_{lo} \qquad (2)$$

Where,

W_{lo} → weighting factors,
E_{lo} → Error distances,
dim_1 → Original Image width,
dim_2 → Original Image height,
l → Sub band level, $l \in \{1, 2\}$,
o → Sub bandorientation,$\in \{1, 2, 3, 4\}$.

The score obtained using the above formulae is in numeric format and is directly proportional to the quality of the image. More the score, better is the image quality.

6. Results

The graphic user interface (GUI) is developed using Matlab 2013, tocalculate the image quality metrics using - PSO, SNR, PSNR, SSIM, UQI. The scores obtained are shown in the table corresponding to each metric and query image respectively in the GUI. Also the image quality score per query image is calculated using PSO-GSA and the obtained results in the text boxes adjacent to "Query Image #1" and "Query Image #2" labels, respectively, in the "Our Algorithm" panel in the GUI.

As a test case we considered 4th reference image from the TID2013 database as the original reference image. Query Image #1 is of "Additive Gaussian noise" type, with distortion number 1 and distortion level 1. [10] Query Image #2 is of "Additive Gaussian noise" type with distortion number 1 and distortion level 3. MOS of Query Image #1 is 5.76190. MOS of Query Image #2 is 4.92857. Thus, Query Image #1 is of better quality than Query Image #2 as predicted by all the metrics.

As a test case we have considered 4th reference image from the TID2013 database as the original reference image. Query Image #1 is of "Image denoising" type distortion (distortion number 9) and distortion level is 5. Query Image #2 is of "Quantization noise" type distortion (distortion number 7) and distortion level is 5. MOS of Query Image #1 is 2.5. MOS of Query Image #2 is 2.95238. Thus, Query Image #2 is of better quality than Query Image #1. All algorithms except Hybrid are calculating less score for Query Image #2. In this case we can say that Hybrid Algorithm gives accurate scores than PSO, PSOGSA, SSIM, SNR, and PSNR, after that we considered 4th reference image from the TID2013 database as the original reference image. Query Image #1 is of "Local block-wise distortions of different intensity" type distortion (distortion number 15) and distortion level is 1. Query Image #2 is of "Spatially correlated noise" type distortion (distortion number 3) and distortion level is 2. MOS of Query Image #1 is 3.38095. MOS of Query Image #2 is 4.21429. Thus, Query Image #2 is of better quality than Query Image #1. But as shown in Fig. 4.4 the algorithms Hybrid and PSO are calculating more score for Query Image #2.

6.1 Average Time

Average time required to calculate each of the objective measures described before isgiven in Table 3. [11]Total time required for each image quality assessment metricwas calculated over entire TID2013 database and then averaged.

Table 3: Average time

Measure	Time (in sec)
IQA_PSOGSA	**0.0173898581**
IQA_PSO	**0.0174913307**
SSIM	**0.0259052782**
SNR	**0.0023755437**
PSNR	**0.0013457383**

As seen from the above results IQA_PSOGSA computes the score faster than SSIM andUQI, in almost half the time.

7. Conclusion

In this paper a technique to assess the quality of an image using PSOGSA algorithm is presented. We proposed a new image quality measure based onDWT in different wavelet sub-bands and PSO-GSA. Our image quality measures takes intoaccount properties of human visual system and provide better results than some otherquality measures. It also works well with image databases like TID2013.Proposed measure can also be considered as a good starting point for evaluation andfair comparison of different types of image degradation, especially in applicationswhere image quality evaluation should be performed in real-time.

References

[1] S. Grgic, M. Grgic and B. Zovko-Cihlar, "Performance analysis of image compression using wavelets," *IEEE Transactions on Industrial Electronics*, vol. 48, no. 3, pp. 682-695, 2001.

[2] N. Damera-Venkata, T. Kite, W. Geisler, B. Evans and A. B. 3+6, "Image quality assessment based on a degradation model," Image Processing," *IEEE Transactions on*, vol. 9, no. 4, pp. 636-650, 2000.

[3] N. Ponomarenko, O. Ieremeiev, V. Lukin, K. Egiazarian, L. Jin, J. Astola, B. Vozel, K. Chehdi, M. Carli, F. Battisti and C.-C. Kuo, "Color image database TID2013: Peculiarities and preliminary results," in *Visual Information Processing (EUVIP), 2013 4th European Workshop on*, 2013.

[4] E. Dumic, S. Grgic and M. Grgic, "Improved image quality measure through particle swarm optimization," in *in Systems, Signals and Image Processing (IWSSIP), 2011 18th International Conference on*, 2011.

[5] G. Strang and T. Nguyen, "Wavelets and Filter Banks," in *Wellesley College*, 1996.

[6] M. G. E. Schneiders, "Wavelets in control engineering.," in *Master's thesis*, 2001.

[7] J. Kennedy and R. C. Eberhart, "Particle swarm optimization", Proc," *IEEE Int'l. Conf. on Neural Networks, IV*, 1942.

[8] H. R. Sheikh, M. F. Sabir and A. C. Bovik, "A Statistical Evaluation of Recent Full Reference Image Quality Assessment Algorithms," *IEEE Transactions on Image Processing*, vol. 15, no. 11, pp. 3440-3451, 2006.

[9] M. Clerc and J. Kennedy, "The Particle Swarm – Explosion, Stability and Convergence in Multidimensional Complex Space," *IEEE Transactions on Evolutionary Computation*, vol. 6, pp. 58-73, 2002.

[10] E. Dumic, S. Grgic and M. Grgic, "New Image-quality Measure based on Wavelets," *Journal of Electronic Imaging, Article ID 011018*, vol. 19, no. 1, p. pages , 2010.

[11] J. Hauke and T. Kossowski, "Comparison of values of Pearson's and Spearman's correlation coefficient on the same sets of data," in *Proceedings of the MAT TRIAD 2007 Conference*, 2007.