A New Method of Image Quality Assessment

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Abstract: In image processing, one of the important items is how to measure the quality of an image. This paper attempts to establish an assessment model corresponding to mean human perception, or mean opinion score (MOS). Human vision system has a feature of being more sensitive to the brightness change of an area than to that of discrete points, and being more sensitive to the change of moderate brightness than to the change of very bright one and very dark one. According to such a feature, by defining brightness discrimination and error density, using gradient as well, this paper proposes a new method of image quality assessment. The new method is tested on TID2008 data and the results are compared with those of existing methods.

Key–Words: image quality assessment, brightness discrimination, error density, gradient

1 Introduction

Along with the recent advances in digital imaging and communication technologies, the levels of the image acquisition, processing, compression, storage and transmission have been significantly improved. However, no matter how good equipments are used, the degeneration of image in above processes is unavoidable. As a result, it is necessary to establish a uniform assessment system which can well correspond to the subjective score by human beings [1, 10, 11, 20, 21, 23]. According to the amount of information from real scenes, image quality assessments are classified as full-reference ones, no-reference ones and reduced-reference ones [2]. We here study the problem of image quality assessment with full-reference [14].

In present literatures, there are four kinds of models to solve the problem of image quality assessment with full-reference. The first kind are based on principles of statistics, such as mean square error (MSE) [22] and peak value signal to noise ratio (PSNR) [2]. The traditional statistical methods are widely used because of the simplicity and definite physical meaning. The second kind use analysis of the structure information of images, such as weighted-peak signal to noise ratio (WSNR) [3, 4], noise quality measures (NQM) [4], universal quality index (UQI) [5], visual signal to noise ratio (VSNR) [12]and structural similarity (SSIM) [2, 6, 7, 13, 17]. Such models are obviously superior to the traditional statistical models because they focus on the sensitivity of human vision to, as well as on the structure information composed of, different parts of an image. The third kind pay main attention to the natural scene of images, such as visual information fidelity (VIF) [9], information fidelity criterion (IFC) [8]. These methods mainly use wavelet transform to extract and compare the scene information of the original image and the degraded image. Such methods are more accurate to images degraded by changes of brightness and contrast. The last kind use feature similarity (FSIM) based on image texture analysis and representative methods [15]. Liu et.al have proposed phase congruency [19] and gradient modulus [18], combined such important information as brightness [15]. These methods are comprehensive and of higher accuracy.

In this paper, we propose a new method of image quality assessment based on brightness discrimination, error density and gradient (BDEDG). According to the feature of human vision system, human beings are more sensitive to the brightness change of an area than that of discrete points, so we define the error density of an area in an image. In addition, because the human beings are more sensitive to the change of appropriate brightness than to that of very bright or very dark scenes, we define the brightness discrimination to measure the sensitivity. Making use of error density, brightness discrimination and gradient of an image, we establish the model BDEDG to measure the quality of the image. The proposed BDEDG is tested on TID2008 database [16]. Compared with some current state-of-art methods, our method gives a satisfying performance.

The rest of the paper is organized as follows. In Section 2, the detail of the proposed method BDEDG is presented. The experiments results and comparisons are shown in Section 3. Finally, the conclusion is given in Section 4.

2 The proposed BDEDG

It is a fact that the sensitivity of human vision to different areas with different texture densities and different brightness is different. Therefore we propose a new image quality assessment based on brightness discrimination, error density and gradient (BDEDG).

Denote the original image as $I_{ori} = (I_{ori}(i,j))_{S\times T}$ and the degraded image as $I_{deg} = (I_{deg}(i,j))_{S\times T}$. The absolute difference between I_{ori} and I_{deg} is

$$Error(i,j) = |I_{ori} - I_{deg}|, i = 1, ..., S, j = 1, ..., T.$$

Obviously, it will not cause any significant response of human vision system even if Error(i,j) are very large on some individual points. That is to say, human vision is sensitive to the brightness change of an area instead of individual points. So we define the error density of point (i,j) as

$$DError(i,j) = \frac{1}{(2w+1)^2}\sum_{s=i-w}^{i+w}\sum_{t=j-w}^{j+w} Error(s,t),$$

where the local area of size $(2w+1)\times(2w+1)$ centers at (i,j).

Usually human vision is not sensitive to the brightness change in very bright or very dark areas of an image, but sensitive to the change of appropriate brightness. So we define the brightness discrimination to measure the sensitivity of human vision to brightness as

$$Bd(i,j) = \Phi(\frac{I_{ori}(i,j)}{255}), i = 1, ..., S, j = 1, ..., T,$$

where $\Phi(x) = x(1-x)$. The value of Bd is small when the brightness is too high or too low.

Another fact is that human vision is more sensitive to the brightness change in the smooth area than in the area of complicated texture. So it is reasonable to take the gradient modulus $G(i,j) = gradient(I_{ori}(i,j)), i = 1, ..., S, j = 1, ..., T$ into consideration.

Thus we define a new image quality assessment based on brightness discrimination, error density and gradient (BDEDG) as

$$\gamma = \frac{1}{S\times T}\sum_{i,j}\frac{[Bd(i,j)\cdot Error(i,j)\cdot DError(i,j)]^{\lambda_1}}{[G(i,j)+c]^{\lambda_2}},$$

$$BDEDG = exp(-\lambda_3\gamma).$$

Where $\lambda_1, \lambda_2, \lambda_3, c > 0$. The parameter c is a small value to ensure that the denominator isn't zero.

3 Experimental results

TID2008 database includes totally 1700 distorted images which degenerate from 25 original images and 17 kinds of distortion with 4 levels. There are 100 images distorted by one kind of distortion. Specifically, 17 kinds of distortion are: 1-additive Gaussian noise, 2-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) and 17-contrast change.

When make test on TID2008 database, for one model of quality assessment and one kind of distortion, we calculate the correlation coefficient of the 100 scores gotten by this assessment and the corresponding 100 scores in MOS. So we have 17 correlation coefficients for one model of quality assessment tested on TID2008.

To compare two sets of data, correlation analysis methods are used. Here, correlation analysis aims to evaluate the effectiveness of an objective assessment method by comparing the result with the subjective score given by human beings. Three methods are widely used for correlation analysis: Spearman Rank Order Correlation Coefficient (SROCC), Kendall Rank Order Correlation Coefficient (KROCC) and Pearson Linear Correlation Coefficient (PLCC) [23].

To find the optical optimal values of the parameters in BDEDG, 5 values of λ_1, 5 values of λ_2 and 15 values of λ_3 are tested. Let $\lambda_1, \lambda_2 = 0.25, 0.5, 1, 2, 3$, and $\lambda_3 = 0.1 : 0.1 : 1.5$. For every set of values of (λ_1, λ_2), find the best value of λ_3. The results are shown in table I, where the results in the cell of the ith line and jth row are calculated with $\lambda_1 = \lambda_1(i), \lambda_2 = \lambda_2(j)$. In every (i,j) cell, the value of λ_3 is the best value (not necessarily unique), where P, S and K represent the numbers of superiors of BDEDG compared to other 11 models corresponding to the 3 kinds of correlation respectively. Note that, for each kind of correlation, there are 187 correlation coefficients for 11 assessment models and 17 kinds of distortion. In Table 1, computation shows that (1,3,1) is the optimal set of parameter $(\lambda_1, \lambda_2, \lambda_3)$.

The proposed BDEDG model is tested on TID2008 database, and the result is compared with 11 current state-of-art methods of image quality assessment with full-reference. Correlation coefficients computed with BDEDG in sense of SROCC, KROCC and PLCC are displayed in Table 2-4 respectively.

As shown in Table 2, the SROCC values of BDEDG, among the 17 kinds of image distortion, are superior to MSE, PSNR, SSIM, MSSIM, NQM, SNR, UQI, VIF, VIFP, VSNR, WSNR in 11,11,9,8,15,14,13,11,11,15,11 cases respectively.

As shown in Table 3, the KROCC values of BDEDG, among the 17 kinds of image distortion, are superior to MSE, PSNR, SSIM, MSSIM, NQM, SNR, UQI, VIF, VIFP, VSNR, WSNR in 11,11,9,9,13,13,14,10,11,16,12 cases respectively.

As shown in Table 4, he PLCC values of BDEDG, among the 17 kinds of image distortion, are superior to MSE, PSNR, SSIM, MSSIM, NQM, SNR, UQI, VIF, VIFP, VSNR, WSNR in 12,12,11,12,14,14,12,12,12,16,12 cases separately.

In summary, our method BDEDG gives a satisfying performance on database TID2008.

4 Conclusion

In this paper, we study the problem of image quality assessment with full-reference. We propose a new method of image quality assessment based on brightness discrimination, error density and gradient (BDEDG). We test our proposed method BDEDG on TID2008 database, compared it with 11 current state-of-art methods of image quality assessment with full-reference by computing the correlation coefficients of SROCC, KROCC and PLCC separately. The experiments have shown that our method BDEDG performs very well on TID2008 database.

References:

[1] W. Zhou and A. C. Bovik, *Modern image quality assessment,* New York: Morgan and Claypool Publishing Company, 20-30, 2006.

[2] W. Zhou, A. C. Bovik, H. R. Sheikh, et al., Image quality assessment: from error visibility to structure similarity, *IEEE Trans. on Image Processing,* 13(4), 2004, pp. 600–612, .

[3] T. Mitsa and K. Varkur, Evaluation of contrast sensitivity functions for the formulation of quality measures incorporated in half toning algorithms, *ICASSP* 1993, pp. 301–304.

[4] N. Damera-Venkata, T. D. Kite, W. S. Geisler, et al., Image quality assessment based on a degradation model, *IEEE Trans. on Image Processing* 9, 2000, pp. 636–650.

[5] W. Zhou and A. C. Bovik, A universal image quality index, *IEEE Trans on. Signal Processing Letters* 9, 2002, pp. 81–84.

[6] W. Zhou, P. Simoncelli, A. C. Bovik and H. R. Sheikh, Multiscal structure similarity for image quality assessment, *Proc. of the 37th Asilomar Conference on Signals, Systems and Computers*, 2003, pp. 1398–1402.

[7] G. Chen, C. Yang and Xie S.,, Gradient-based structure similarity for image quality assessment., *Proc. Of International Conference on Image Processing*, 2006, pp. 2929–2932.

[8] H. R. Sheikh, A. C. Bovic and De Veciana G.,, An information fidelity criterion for image quality assessment using natural scene statistics, *IEEE Tans. on Image Processing* 14, 2005, pp. 2117–2128.

[9] H. R. Sheikh and A. C. Bovic, Image information and visual quality, *IEEE Trans. on Image Processing* 15, 2006.

[10] A. B. Watson, DCTune: A technique for visual optimization of DCT quantization matrices for individual images, *Society for Information Display Digest of Technical PapersXXIV*, 1993, pp. 946–949.

[11] S. Lee, M. S. Pattichis and A. C. Bovik,, Foveated Video Quality Assessment, *IEEE Trans. on Image Multimedia* 4, 2002.

[12] D. M. Chandler and S. Hemami, VSNR: A wavelet-based visual signal-to-noise ratio for natural images, *IEEE Tran. on Image Processing* 16, 2007.

[13] C. Li and A. C. Bovik, Content-partitioned structural similarity index for image quality assessment, *Signal Processing: Image Communication* 25, 2010, pp. 517–526.

[14] E. C. Larson and D. M. Chandler, Most apparent distortion: full-reference image quality assessment and the role of stratege, *Journal of Electronic Imaging* 19, 2010.

[15] L. Zhang, X. Mou and D. Zhang, FSIM: A feature similarity index for image quality assessment, *IEEE Tran. on Image Processing* 20, 2011.

[16] N. Ponomarenko, V. Lukin, A. Zelensky, K. Egiazarian, M. Carli and F. Battisti, TID2008-A database for evaluation of full-reference visual quality assessment metrics, *Adv. Modern Radioelectron* 10, 2009, pp. 30–45.

[17] M. P. Sampat, Z. Wang, S. Gupta, A. C. Bovik and M. K. Markey, Complex wavelet structural similarity: A new image similarity index, *IEEE Trans. on Image Processing* 18, 2009, pp. 2385–2401.

[18] D. Marr and E. Hildreth, Theory of edge detection, *Proc. R. Soc. Lond. B* 207, 1980, pp. 187–217.

[19] P. Kovesi, Image features from phase congruency, *Videre: J. Comp. Vis. Res.* 1, 1999, pp. 1–26.

[20] A. M. Eskicioglu and P. S. Fisher, Image quality measures and their performance, *IEEE Trans. On Comm.* 43, 1995, pp. 2959–2965.

[21] M. P. Eckert and A. P. Bradley, Perceptual quality metrics applied to still image compression, *Signal Processing* 70, 1998, pp. 177–200.

[22] B. Girod, *What's wrong with mean-squared error. Digital Images and Human Vision,* MA: MIT Press, A. B. Watson, Ed. Cambridge, 1993.

[23] A. Liu, W. Lin and M. Narwaria, Image Quality Assessment Based on Gradient Similarity, *IEEE Trans. on Image Processing* 21, 2012.

Table 1: Parameter selection in BDEDG

Lamda_3=0.7 P=118 S=106 K=101 Total=325	Lamda_3=1 P=120 S=106 K=105 Total=331	Lamda_3=0.6 0.7 P=115 S=111 K=110 Total=336	Lamda_3=0.2 P=103 S=90 K=89 Total=282	Lamda_3=0.1 P=80 S=69 K=73 Total=222
Lamda_3=0.8 0.9 P=126 S=112 K=112 Total=350	Lamda_3=0.8 0.9 P=124 S=122 K=119 Total=365	Lamda_3=0.2 0.3 P=129 S=128 K=129 Total=386	Lamda_3=0.3 P=135 S=126 K=128 Total=389	Lamda_3=0.2 P=132 S=125 K=122 Total=379
Lamda_3=0.7 1 P=122 S=118 K=115 Total=355	Lamda_3=0.6 1 P=124 S=118 K=116 Total=358	Lamda_3=0.5 1 P=122 S=121 K=125 Total=368	Lamda_3=0.8 1 P=127 S=127 K=129 Total=383	**Lamda_3=1** **P=133** **S=127** **K=129** **Total=389**
Lamda_3=0.8 0.9 P=82 S=114 K=101 Total=287	Lamda_3=0.1 1 P=80 S=106 K=103 Total=289	Lamda_3=0.9 1 P=79 S=108 K=112 Total=299	Lamda_3=1 P=78 S=108 K=115 Total=301	Lamda_3=1 P=77 S=111 K=114 Total=302
Lamda_3=0.1 1 P=60 S=100 K=105 Total=265	Lamda_3=0.1 1 P=59 S=102 K=106 Total=267	Lamda_3=0.1 1 P=62 S=102 K=109 Total=273	Lamda_3=0.1 1 P=61 S=102 K=110 Total=273	Lamda_3=0.1 1 P=60 S=103 K=109 Total=272

Table 2: Comparison of results in the sense of SROCC

distortion	BDEDG	MSE	PSNR	SSIM	MSSIM	NQM	SNR	UQI	VIF	VIFP	VSNR	WSNR
1	0.9319	**0.9115**	0.9327	**0.8310**	**0.8094**	**0.7679**	**0.8338**	**0.5161**	**0.8800**	**0.8005**	**0.7728**	**0.8714**
2	0.8911	0.9068	0.9068	**0.8134**	**0.8064**	**0.7490**	**0.8513**	**0.4584**	**0.8785**	**0.8357**	**0.7793**	**0.8220**
3	0.9356	**0.9229**	**0.9229**	**0.8438**	**0.8195**	**0.7720**	**0.8332**	**0.5359**	**0.8703**	**0.8414**	**0.7665**	**0.8483**
4	0.8748	**0.8487**	**0.8487**	**0.7561**	**0.8155**	**0.7067**	**0.6995**	**0.7269**	**0.8698**	**0.8429**	**0.7295**	**0.6118**
5	0.9114	0.9323	0.9323	**0.8919**	**0.8685**	**0.9015**	**0.9050**	**0.6722**	**0.9075**	**0.8811**	**0.8811**	0.9129
6	0.8518	0.9177	0.9177	**0.7072**	**0.6868**	**0.7616**	**0.8776**	**0.4950**	**0.8331**	**0.7994**	**0.6471**	0.8941
7	0.8888	**0.8699**	**0.8699**	**0.8745**	**0.8537**	**0.8209**	**0.8205**	**0.5606**	**0.7956**	**0.7903**	**0.8270**	**0.8648**
8	0.8961	**0.8682**	**0.8682**	0.9596	0.9607	**0.8846**	**0.8173**	**0.8836**	0.9546	0.9449	0.9330	0.9326
9	0.9465	**0.9381**	**0.9381**	0.9595	0.9571	**0.9450**	**0.9123**	**0.7754**	**0.9189**	**0.9185**	**0.9286**	**0.9338**
10	0.9342	**0.9011**	**0.9011**	**0.9270**	0.9348	**0.9075**	**0.8054**	**0.7701**	**0.9170**	**0.9150**	**0.9174**	**0.9218**
11	0.9373	**0.8300**	**0.8300**	0.9723	0.9736	0.9532	**0.7837**	**0.9116**	0.9713	0.9588	0.9515	0.9566
12	0.8211	**0.7665**	**0.7665**	0.8668	0.8736	**0.7373**	**0.7215**	0.8348	0.8582	0.8386	**0.8055**	**0.7382**
13	0.8841	**0.7765**	**0.7765**	**0.8707**	**0.8525**	**0.7262**	**0.7952**	**0.6714**	**0.8510**	**0.8325**	**0.7909**	**0.8335**
14	0.7108	**0.5931**	**0.5931**	0.7168	0.7336	**0.6800**	**0.5022**	0.7398	0.7608	0.7701	**0.5716**	**0.6891**
15	0.3918	0.5852	0.5852	0.8529	0.7617	**0.2348**	0.4016	0.8070	0.8320	0.8352	**0.1926**	**0.2907**
16	0.6237	0.6974	0.6974	0.7575	0.7374	**0.5245**	0.7603	**0.5617**	**0.5132**	**0.5106**	**0.3715**	0.7588
17	0.5044	0.6126	0.6126	0.6329	0.6400	0.6191	0.5948	0.5201	0.8190	0.8075	**0.4239**	0.5722

Table 3: Comparison of results in the sense of KROCC

distortion	BDEDG	MSE	PSNR	SSIM	MSSIM	NQM	SNR	UQI	VIF	VIFP	VSNR	WSNR
1	0.9227	**0.9028**	0.9327	**0.7669**	**0.7477**	**0.7455**	**0.8097**	**0.5238**	**0.8667**	**0.7774**	**0.7448**	**0.8531**
2	0.9053	0.9079	0.9219	**0.7853**	**0.7781**	**0.7345**	**0.8430**	**0.4629**	**0.8953**	**0.8291**	**0.7639**	**0.8116**
3	0.9359	**0.9154**	0.9523	**0.7957**	**0.7602**	**0.7573**	**0.8176**	**0.5440**	**0.8585**	**0.8330**	**0.7500**	**0.8346**
4	0.8837	**0.8635**	**0.8617**	**0.7308**	**0.7873**	**0.7084**	**0.6815**	**0.7555**	**0.8915**	**0.8493**	**0.7530**	**0.5976**
5	0.9491	**0.9138**	0.9673	**0.8208**	**0.8220**	**0.9161**	**0.9071**	**0.6898**	**0.9451**	**0.8753**	**0.8832**	**0.9191**
6	0.8483	0.8762	0.9063	**0.6320**	**0.6250**	**0.7438**	0.8583	**0.4794**	**0.8149**	**0.7836**	**0.6242**	0.8817
7	0.8746	**0.8438**	0.8903	**0.7906**	**0.7567**	**0.8073**	**0.8049**	**0.5505**	**0.7453**	**0.6802**	**0.8130**	**0.8494**
8	0.8618	**0.4870**	**0.8376**	0.8782	0.8774	0.8731	**0.8118**	0.8749	0.9392	0.9416	0.9160	0.9309
9	0.9431	**0.8318**	**0.9412**	**0.9135**	**0.9148**	0.9549	**0.9066**	**0.8011**	**0.8975**	**0.8948**	**0.9194**	**0.9347**
10	0.9327	**0.7679**	**0.8892**	**0.9300**	**0.9310**	**0.9203**	**0.7892**	**0.7885**	**0.9324**	**0.9188**	**0.9058**	**0.9296**
11	0.9475	**0.8522**	**0.8657**	**0.9516**	**0.9386**	0.9524	**0.7794**	**0.9189**	**0.9171**	**0.9412**	**0.9343**	0.9518
12	0.7823	**0.7247**	**0.7653**	0.8276	0.8241	**0.7332**	**0.5925**	0.8378	0.8719	0.8537	**0.6466**	**0.7207**
13	0.8805	**0.7244**	**0.7874**	**0.8310**	**0.7876**	**0.7341**	**0.8036**	**0.6790**	**0.8310**	**0.8180**	**0.7610**	**0.8354**
14	0.7199	**0.5506**	**0.5975**	**0.6608**	**0.6646**	**0.6822**	**0.5107**	0.7212	0.7363	0.7538	**0.5658**	**0.6791**
15	0.4219	0.5250	0.5735	0.8720	0.7962	**0.2144**	**0.4112**	0.8430	0.8336	0.8452	**0.2727**	**0.2654**
16	0.6027	0.7004	0.6819	0.7267	0.6690	**0.5251**	0.7307	**0.4242**	**0.5920**	**0.5945**	**0.2469**	0.7292
17	0.4891	0.5915	0.6043	0.7004	0.7688	0.6283	0.6049	0.5335	0.8832	0.8492	**0.4285**	0.5946

Table 4: Comparison of results in the sense of PLCC

distortion	BDEDG	MSE	PSNR	SSIM	MSSIM	NQM	SNR	UQI	VIF	VIFP	VSNR	WSNR
1	0.7600	**0.7207**	**0.7207**	**0.6321**	**0.6095**	**0.5626**	**0.6325**	**0.3591**	**0.6792**	**0.6019**	**0.5617**	**0.6754**
2	0.7050	0.7289	0.7289	**0.6165**	**0.6045**	**0.5524**	**0.6580**	**0.3097**	**0.6942**	**0.6480**	**0.5844**	**0.6184**
3	0.7589	**0.7298**	**0.7298**	**0.6464**	**0.6160**	**0.5611**	**0.6254**	**0.3774**	**0.6784**	**0.6440**	**0.5611**	**0.6436**
4	0.6791	**0.6336**	**0.6336**	**0.5647**	**0.6219**	**0.5189**	**0.4930**	**0.5263**	0.6923	**0.6479**	**0.5435**	**0.4464**
5	0.6907	0.7465	0.7465	**0.6686**	**0.6377**	0.7064	0.7036	**0.4555**	**0.6741**	**0.6530**	**0.6607**	0.7250
6	0.6493	0.7512	0.7512	**0.5072**	**0.4846**	**0.5441**	0.6913	**0.3311**	**0.6284**	**0.5856**	**0.4523**	0.7156
7	0.7057	**0.6788**	**0.6788**	**0.6924**	**0.6625**	**0.6251**	**0.6150**	**0.3999**	**0.6479**	**0.6412**	**0.6348**	**0.6684**
8	0.7862	**0.7328**	**0.7328**	0.8288	0.8271	**0.6783**	**0.6475**	**0.6758**	0.8205	0.7878	**0.7733**	**0.7717**
9	0.7905	**0.7804**	**0.7804**	0.8332	0.8304	0.7921	**0.7387**	**0.5775**	**0.7610**	**0.7633**	**0.7638**	**0.7674**
10	0.7736	**0.7308**	**0.7308**	**0.7334**	**0.7580**	**0.7142**	**0.6035**	**0.5445**	**0.7195**	**0.7404**	**0.7344**	**0.7300**
11	0.7824	**0.6382**	**0.6382**	0.8573	0.8656	0.8034	**0.5767**	**0.7415**	0.8515	0.8215	0.8042	0.8152
12	0.6212	**0.5788**	**0.5788**	0.6669	0.6796	**0.5388**	**0.5210**	0.6332	0.6572	0.6345	**0.5978**	**0.5388**
13	0.7139	**0.5893**	**0.5893**	**0.6876**	**0.6622**	**0.5294**	**0.5965**	**0.4825**	**0.6593**	**0.6369**	**0.5982**	**0.6470**
14	0.5084	**0.4191**	**0.4191**	0.5114	0.5238	**0.4737**	**0.3463**	0.5446	0.6001	0.6052	**0.3989**	**0.4890**
15	0.2902	0.4189	0.4189	0.6584	0.5515	**0.1635**	**0.2837**	0.5947	0.6215	0.6171	**0.1350**	**0.2117**
16	0.4336	0.5007	0.5007	0.5678	0.5525	**0.3705**	0.5658	**0.4080**	**0.3523**	**0.3522**	**0.2572**	0.5638
17	0.3446	0.4340	0.4340	0.4761	0.4830	0.4178	0.4433	**0.3246**	0.5798	0.5713	**0.2787**	0.4105