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RELIABILITY OF OBJECTIVE PICTURE QUALITY MEASURES

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This paper investigates a set of objective picture quality measures for application in still image compression systems and emphasizes the correlation of these measures with subjective picture quality measures. Picture quality is measured using nine different objective picture quality measures and subjectively using Mean Opinion Score (MOS) as measure of perceived picture quality. The correlation between each objective measure and MOS is found. The effects of different image compression algorithms, image contents and compression ratios are assessed. Our results show that some objective measures correlate well with the perceived picture quality for a given compression algorithm but they are not reliable for an evaluation across different algorithms. So, we compared objective picture quality measures across different algorithms and we found measures, which serve well in all tested image compression systems.

K e y w o r d s: correlation, JPEG, JPEG2000, objective assessment, picture quality measures, SPIHT

1 INTRODUCTION

With the increasing use of multimedia technologies, image compression requires higher performance. To address needs and requirements of multimedia and Internet applications, many efficient image compression techniques, with considerably different features, have recently been developed. Image compression techniques exploit a common characteristic of most images that the neighboring picture elements (pixels, pels) are highly correlated [1]. It means that a typical still image contains a large amount of spatial redundancy in plain areas where adjacent pixels have almost the same values. In addition, still image can contain subjective redundancy, which is determined by properties of human visual system (HVS). HVS presents some tolerance to distortion depending upon the image content and viewing conditions. Consequently, pixels must not always be reproduced exactly as originated and HVS will not detect the difference between original image and reproduced image [2]. The redundancy (both statistical and subjective) can be removed to achieve compression of the image data. The basic measures for the performance of a compression system are picture quality and compression ratio (defined as ratio between original data size and compressed data size). In lossy compression scheme, image compression algorithm should achieve trade off between compression ratio and picture quality. Higher compression ratios will produce lower picture quality and vice versa.

The evaluation of lossless image compression techniques is a simple task where compression ratio and execution time are employed as standard criteria. The picture quality before and after compression is unchanged. Contrary, the evaluation of lossy techniques is difficult task because of inherent drawbacks associated with both objective and subjective measures of picture quality. Objective measures of picture quality do not correlate well with subjective quality measures [3], [4]. Subjective assessment of picture quality is time consuming process and results of measurements should be processed very carefully. In many applications (photos, medical images where loss is tolerated, network applications, World Wide Web, *etc.*) it is very important to choose image compression system which gives the best subjective quality, but the quality has to be evaluated objectively. Therefore, it is important to use objective picture quality measure, which has high correlation with subjective picture quality.

In this paper we attempt to evaluate and compare objective and subjective picture quality measures. As test images we used images with different spatial and frequency characteristics. Images are coded using JPEG, JPEG2000 and SPIHT compression algorithms. The paper is structured as follows. In section 2 we define picture quality measures. In section 3 we briefly present image compression systems used in our experiment. In Section 4 we evaluate statistical and frequency properties of test images. Section 5 contains numerical results of picture quality measures. In this section we analyze correlation of objective measures with subjective grades and we propose objective measures, which should be used in relation to each image compression system, and objective measures, which are suitable for the comparison of picture quality between different compression systems.

2 PICTURE QUALITY MEASURES

Among many objective numerical measures of picture quality, that are based on computable distortion measures, we have chosen those listed in Table 1. All measures are discrete and they provide some degree of closeness between two digital images by exploiting the differences in the statistical distributions of pixel values.

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Table 1. Picture quality measures

Mean Square Error	$MSE = \frac{1}{MN} \sum_{j=1}^{M} \sum_{k=1}^{N} \left(x_{j,k} - x'_{j,k} \right)^2$
Peak Signal to Noise Ratio	$PSNR = 10 \log \frac{(2^n - 1)^2}{MSE} = 10 \log \frac{255^2}{MSE}$
Normalized Cross-Correlation	$NK = \sum_{j=1}^{M} \sum_{k=1}^{N} x_{j,k} \cdot x'_{j,k} \Big/ \sum_{j=1}^{M} \sum_{k=1}^{N} x_{j,k}^2$
Average Difference	$AD = \sum_{j=1}^{M} \sum_{k=1}^{N} \left(x_{j,k} - x'_{j,k} \right) \Big/ MN$
Structural Content	$SC = \sum_{j=1}^{M} \sum_{k=1}^{N} {x_{j,k}}^2 \Big/ \sum_{j=1}^{M} \sum_{k=1}^{N} {x'_{j,k}}^2$
Maximum Difference	$MD = Max \left(\left| x_{j,k} - x'_{j,k} \right| \right)$
Laplacian Mean Square Error	$LMSE = \sum_{j=1}^{M} \sum_{k=1}^{N} \left[O\left(x_{j,k}\right) - O\left(x'_{j,k}\right) \right] \Big/ \sum_{j=1}^{M} \sum_{k=1}^{N} \left[O\left(x_{j,k}\right) \right]^2$ $O\left(x_{j,k}\right) = x_{j+1,k} + x_{j-1,k} + x_{j,k+1} + x_{j,k-1} - 4x_{j,k}$
Normalized Absolute Error	$NAE = \sum_{j=1}^{M} \sum_{k=1}^{N} \left| x_{j,k} - x'_{j,k} \right| \Big/ \sum_{j=1}^{M} \sum_{k=1}^{N} \left| x_{j,k} \right|$
Picture Quality Scale	$PQS = b_0 + \sum_{i=1}^{3} b_i Z_i$

In our analysis, the digital image is represented as $M \times N$ matrix, where M denotes the number of columns and N the number of rows. While the pixel coordinate in image is (j,k), $x_{j,k}$ and $x'_{j,k}$ denote the pixel values of original image before the compression and degraded image after the compression.

Mean squared error (MSE) and Peak Signal to Noise Ratio $(PSNR)$ are the most common measures of picture quality in image compression systems, despite the fact that they are not adequate as perceptually meaningful measures [5]. In addition to objective measures listed in Table 1, we chose to use perception based objective evaluation, quantified by Picture Quality Scale (PQS) [6] and a perception based subjective evaluation, quantified by Mean Opinion Score (MOS) [7]. For the set of distorted images, the MOS values were obtained from an experiment involving 20 non-expert viewers. The testing methodology was the double-stimulus impairment scale method with five-grade impairment scale described in ITU-R BT Rec. 500 [7]. When the tests span the full range of impairments (as in our experiment) the double-stimulus impairment scale method should be used.

The double stimulus impairment scale method uses reference and test conditions, which are arranged in pairs, such that the first in the pair is the unimpaired reference and the second is the same sequence impaired. The original source image without compression was used as the reference condition. The assessor is asked to vote on the second keeping in mind the first. The method uses the five-grade impairment scale with proper description for each grade: 5-imperceptible, 4-perceptible, but not annoying, 3-slightly annoying, 2-annoying and 1-very annoying. At the end of the series of sessions, MOS for each test condition and test image are calculated:

$$MOS = \sum_{i=1}^{5} i\, p\,(i) \tag{1}$$

where i is grade and $p(i)$ is grade probability.

To perform subjective assessment of picture quality we developed an application in Visual Basic, which enables equal viewing conditions for all viewers in our laboratory environment and precisely follows ITU recommendation [7]. Viewing distance was $4H$, where H is image height displayed on monitor in full resolution. 20 non-expert observers assessed a degree of impairment of each test image using five-grade impairment scale with half grade accuracy. Assessors were carefully introduced to the method of assessment, type of impairment, the grading scale and timing. At the beginning of the session "dummy presentations" are introduced to stabilize the observer's opinion. During test session a series of images is presented to assessor in random order. The same test sequence was never presented on two successive presentations with the same or different level of impairment. Some test images were shown twice within the same session to check coherence of viewer results.

(a) Baboon
SFM = 36.515
SAM = 24.93

(b) Goldhill
SFM = 16.167
SAM = 126.77

(c) Lena
SFM = 14.019
SAM = 227.43

Fig. 1. Test images

In addition to MOS, we used PQS methodology proposed in [6]. The PQS has been developed for evaluating the perceived quality of compressed images. It combines various perceived distortions into a single quantitative measure. To do so, PQS methodology uses some of the properties of HVS relevant to global image impairments, such as random errors, and emphasizes the perceptual importance of structured and localized errors. PQS is constructed by regressions with MOS, which is 5-level grading scale. PQS is expressed as a linear combination of uncorrelated principal distortion measures Z_i, combined by partial regression coefficients b_i. PQS closely approximates the MOS in the middle of the quality range [8]. For very high quality images it is possible to obtain values of PQS larger than 5. At the low end of the image quality scale, PQS can obtain negative values (meaningless results).

3 COMPRESSION TECHNIQUES

To produce test images for our objective and subjective picture quality assessments we used three different image compression systems: JPEG [9], [10], JPEG2000 [11], [12] and SPIHT [13]. JPEG (Joint Photographic Experts Group) corresponds to the ISO/IEC international standard 10928-1 for digital compression and coding of continuous-tone (multilevel) still images. Image compression scheme in JPEG is based on Discrete Cosine Transform (DCT) [14].

Much research has been undertaken on still image coding since JPEG standard was established. JPEG2000 is an attempt to focus these research efforts into a new standard for coding still images [7]. JPEG2000 should provide low bit-rate operation (below 0.25 bits/pixel) with subjective picture quality performance superior to existing standards, without sacrificing performance at higher bit rates. Image compression scheme in JPEG2000 Part I is based on discrete wavelet transform (DWT) [15], [16]. In our experiment JJ2000 implementation of JPEG2000 codec is used [17].

Set Partitioning in Hierarchical Trees (SPIHT) coding algorithm introduced by Said and Pearlman is a very efficient technique for wavelet image compression. SPIHT is improved and extended version of Embedded Zerotree Wavelet (EZW) coding algorithm introduced by J. M. Shapiro [18] and it is one of the best wavelet coder today.

4 TEST IMAGES

The fundamental difficulty in testing image compression system is how to decide which test images to use for the evaluations. The image content being viewed influences the perception of quality irrespective of technical parameters of the system [19]. Normally, a series of pictures, which are average in terms of how difficult they are for system being evaluated, has been selected. We have selected three test images (512×512, 8 bits/pixel) that have different spatial and frequency characteristics: Baboon, Goldhill and Lena (shown in Figure 1). The spatial frequency measure (SFM) indicates the overall activity level in an image [20]. SFM is defined as follows:

$$SFM = \sqrt{R^2 + C^2}$$

$$R = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{k=2}^{N}\left(x_{j,k} - x_{j,k-1}\right)^2}$$

$$C = \sqrt{\frac{1}{MN}\sum_{k=1}^{N}\sum_{j=2}^{M}\left(x_{j,k} - x_{j-1,k}\right)^2} \qquad (2)$$

where R is row frequency, C is column frequency and $x_{j,k}$ denotes the samples of image; M and N are numbers of pixels in horizontal and vertical directions. Spectral activity measure (SAM) is a measure of image pre-

Table 2. Assessment results

		JPEG2000			SPIHT			JPEG		
	bpp	$PSNR$	PQS	MOS	$PSNR$	PQS	MOS	$PSNR$	PQS	MOS
Baboon	0.10	21.321	0.213	1.350	21.347	0.307	1.525	19.008	—	1.000
	0.20	22.691	1.119	2.175	22.698	1.008	1.850	20.871	0.594	1.125
	0.30	23.659	1.547	2.350	23.761	1.723	2.250	22.033	1.420	1.425
	0.40	24.678	2.063	2.700	24.656	2.191	2.825	22.819	1.977	1.825
	0.50	25.583	2.325	2.800	25.638	2.364	3.050	23.672	2.537	2.825
	0.75	27.418	2.864	3.200	27.512	3.069	3.450	25.408	3.467	4.200
	1.00	29.110	3.460	3.850	29.162	3.434	3.625	26.446	3.878	4.400
	1.50	32.016	3.968	4.600	32.116	4.041	4.600	28.641	4.422	4.850
	3.00	40.083	4.811	4.950	40.208	4.790	4.875	34.770	5.065	4.975
Goldhill	0.10	27.890	—	1.100	27.927	—	1.200	22.028	—	1.000
	0.20	29.935	0.470	2.075	29.837	—	2.000	26.867	—	1.050
	0.30	31.142	1.385	2.600	31.128	1.473	2.375	29.233	0.655	1.850
	0.40	32.310	2.073	2.925	32.151	2.030	2.850	30.357	1.656	2.750
	0.50	33.244	2.585	3.850	33.089	2.234	3.700	31.310	2.394	3.675
	0.75	35.011	3.376	4.425	34.893	3.322	4.100	33.349	3.615	4.525
	1.00	36.572	3.720	4.800	36.471	3.545	4.625	34.404	4.040	4.800
	1.50	39.189	4.344	4.875	39.062	4.278	4.825	36.477	4.613	4.800
	3.00	47.093	4.905	4.900	46.550	4.833	4.900	41.906	5.157	4.950
Lena	0.10	29.970	—	1.450	30.222	—	1.850	21.928	—	1.000
	0.20	33.052	2.222	2.650	33.140	2.290	2.750	28.896	—	1.225
	0.30	34.918	3.091	3.525	34.935	2.930	3.425	31.681	2.083	1.975
	0.40	36.217	3.502	3.700	36.212	3.585	3.775	33.432	3.025	2.725
	0.50	37.336	3.865	3.950	37.175	3.806	4.250	34.644	3.578	3.350
	0.75	39.022	4.282	4.300	38.963	4.297	4.375	36.749	4.338	4.175
	1.00	40.430	4.534	4.450	10.287	4.493	4.375	37.760	4.612	4.575
	1.50	42.839	4.789	4.800	42.673	4.748	4.650	39.658	4.958	4.775
	3.00	48.818	5.158	4.800	48.683	5.135	4.850	43.595	5.277	4.700

dictability and it is evaluated in frequency domain [1]:

$$SAM = \frac{\frac{1}{M\cdot N}\sum_{j=0}^{M-1}\sum_{k=0}^{N-1}|F(j,k)|^2}{\left[\prod_{j=0}^{M-1}\prod_{k=0}^{N-1}|F(j,k)|^2\right]^{\frac{1}{M\cdot N}}} \qquad (3)$$

where $F(j,k)$ is (j,k)-th DFT coefficient of image. SAM has a dynamic range of $< 1, \infty)$. Higher values of SAM imply higher predictability. Active images (SAM close to 1) are in general difficult to code. These images usually contain large number of small details and low spatial redundancy.

Test image Baboon has a lot of details and consequently large SFM and small SAM. Large value of SFM means that image contains components in high frequency area and small value of SAM means low predictability. It returns that Baboon presents low redundant image, which is difficult for compression. For typical natural image, largest value of SFM implies smaller value of SAM. Images Goldhill and Lena are images with less detail (smaller SFM) than Baboon. Image Goldhill has higher SFM and lower SAM than Lena. It indicates that image Lena has higher predictability than Goldhill.

5 RESULTS

Test images Baboon, Lena and Goldhill are coded using JPEG, JPEG2000 and SPIHT compression algorithms. For each test image and compression method, nine different bit rates are selected: 0.1; 0.2; 0.3; 0.4; 0.5; 0.75; 1; 1.5 and 3 bits per pixel (bpp). Objective and subjective picture quality measures are calculated for all images. Results for $PSNR$, PQS and MOS are presented in Table 2 and Figure 2 for each test image and each compression system. For some very low quality images PQS is out of range. PQS as objective picture quality measure, which incorporates model of HVS, and MOS as subjective picture quality measure, use the same quality scale, so direct comparison between these two measures is possible for different image contents and different compression systems. On the other hand, $PSNR$ values de-

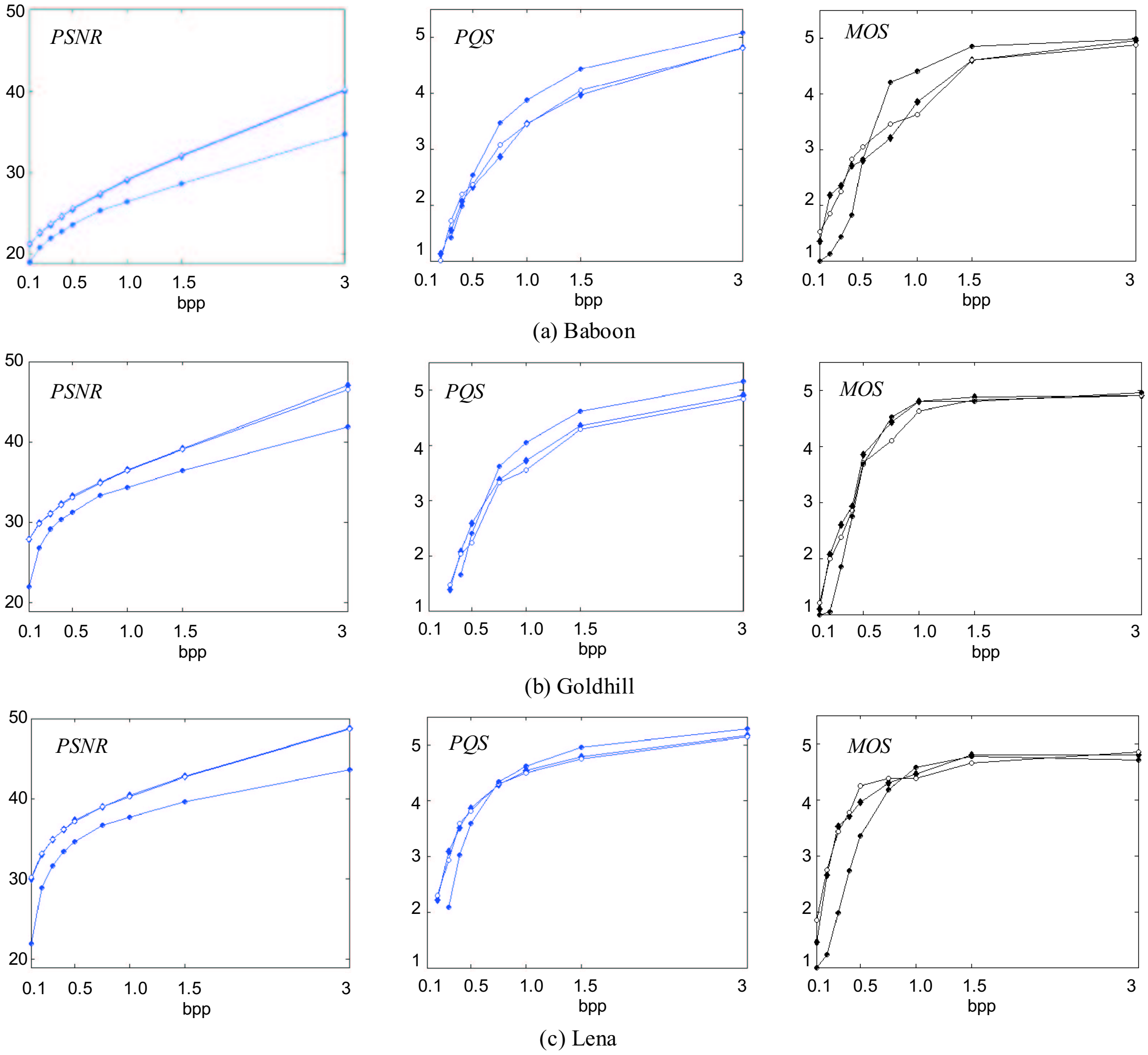

Fig. 2. $PSNR$ (in dB), PQS and MOS results for test images (a) Baboon, (b) Goldhill, (c) Lena, and compression systems denoted as (♦ — JPEG2000; ○ — SPIHT; • — JPEG)

Table 3. Correlation coefficients for each compression technique and test image

Test Image	Codec	MSE	$PSNR$	AD	SC	NK	MD	$LMSE$	NAE	PQS
Baboon	JPEG2000	−0.95506	0.94071	0.84244	−0.92320	0.94264	−0.97625	−0.98814	−0.98912	0.99054
	SPIHT	−0.96117	0.93149	−0.50867	−0.95273	0.95803	−0.98784	−0.98947	−0.98905	0.98951
	JPEG	−0.89973	0.88491	0.38663	−0.94490	0.92001	−0.91574	−0.90406	−0.93453	0.97878
Goldhill	JPEG2000	−0.97097	0.83227	0.69434	−0.96565	0.97000	−0.96746	−0.93256	−0.95399	0.97033
	SPIHT	−0.96723	0.86626	−0.80212	−0.97618	0.97247	−0.96992	−0.96155	−0.96573	0.94765
	JPEG	−0.74839	0.89574	0.50969	0.42746	0.80153	−0.94067	−0.90946	−0.84936	0.97073
Lena	JPEG2000	−0.98327	0.88481	0.71231	−0.95673	0.97326	−0.97585	−0.95612	−0.97600	0.99111
	SPIHT	−0.97636	0.88636	0.85532	−0.97525	0.97609	−0.97765	−0.95429	−0.97363	0.98234
	JPEG	−0.68045	0.93077	−0.43969	0.56470	0.80798	−0.85259	−0.90469	−0.78024	0.98867
Average absolute values of r		0.90	0.89	0.64	0.85	0.92	0.95	0.94	0.93	0.98

pend very much on image content. For example, $PSNR$ of image Lena is through all compression ratios for about 8-11 dB higher than $PSNR$ for image Baboon. $PSNR$ can not be used for quality comparison of different images. Using results presented in Table 2 and Figure 2, we want to illustrate what can happen if only $PSNR$ is used

Fig. 3. Magnified details from images Baboon, Goldhill and Lena compressed at 0.3 bpp

Table 4. Average absolute values of correlation coefficients for each compression system

Codec	MSE	$PSNR$	AD	SC	NK	MD	$LMSE$	NAE	PQS
JPEG2000	0.97	0.89	0.75	0.95	0.96	0.97	0.96	0.97	0.98
SPIHT	0.97	0.89	0.72	0.97	0.97	0.98	0.97	0.98	0.97
JPEG	0.78	0.90	0.45	0.65	0.84	0.90	0.91	0.85	0.98

as objective measure of picture quality. If we consider only $PSNR$ values, we can conclude that JPEG2000 and SPIHT provides better picture quality than JPEG for all test images and all bitrates. If we take into account visual picture quality quantified by MOS, the conclusions are quite different. At high and moderate bitrates (above 0.75 bpp) for all test images JPEG produces better visual picture quality than wavelet-based techniques (JPEG2000 and SPIHT). At low bitrates (below 0.5 bpp) JPEG picture quality degrades below SPIHT and JPEG2000 picture quality, because of the artefacts introduced by block-based DCT scheme. It is clear example that $PSNR$ can not be used as definitive picture quality measure. PQS grades follow the trend of MOS grades but MOS results show that human observers have more tolerance for moderately distorted images than PQS. The results of subjective assessments are strongly influenced by image content and MOS includes psychological effects of HVS that can not be included in PQS.

Figure 3 presents details from compressed test images at 0.3 bpp. At 0.3 bpp visual picture quality is not acceptable for all compression systems because all images have MOS lower than 3. The comparison demonstrates different nature of reconstruction error in DCT compression system used in JPEG and DWT compression system used in JPEG2000 and SPIHT. The block-based segmentation of source image is fundamental limitation of the DCT-based compression system and degradation in reconstructed image is known as "blocking effect". At bitrate of 0.3 bpp wavelet based image coders (JPEG2000 and SPIHT) give much better visual quality then JPEG but these images also have pure quality because of blurriness and ringing artefacts at sharp edges where the intensity abruptly changes. The type of degradation can not be evaluated by objective picture quality measures and subjective assessments are needed to estimate degradation annoyance for human visual system.

Table 3 shows the correlation between the numerical objective quality measures introduced in Table 1 and MOS. As a measure of the extent of the linear relationship, the Pearson product-moment (r) was used [20]. Correlation coefficient is defined as:

$$r = \frac{\sum (x_i - \bar{x})(x'_i - \bar{x}')}{\sqrt{\sum (x_i - \bar{x})^2 \sum (x'_i - \bar{x}')^2}} \tag{4}$$

where x and x' are two series between which correlation has to be found. The possible values of r are between -1 and +1; the closer r is to -1 or +1, the better the correlation is. The last row in Table 3 contains average absolute values of correlation coefficients for each objective measure. The values of correlation coefficients indicate that commonly used measures of visual quality $PSNR$ and MSE can not be reliably used with all techniques, because they have poor correlation with MOS. PQS incorporates model of HVS and leads to the best correlation with MOS for all three compression systems and all test images, but it needs too much time to be evaluated (approximately 15 sec per image in our test). Beside PQS, measures with good correlation with MOS are MD, $LMSE$, NAE and NK (see average absolute values of r in Table 3). MSE, $PSNR$ and SC can not be reliably used with all techniques, because they have poor correlation with MOS for some of them. The poorest correlation has AD.

Different compression techniques introduce different types of degradation into reconstructed images. Since the metrics combine all the pixel difference between two given images into u single number, it is not easy to find measure, which will be good for all compression techniques. To evaluate usefulness of each quality measure in tested compression systems we found average absolute values of correlation coefficients for each compression system. Results are shown in Table 4. Table 4 indicates that PQS is excellent measure of picture quality for all compression systems. In JPEG2000 and SPIHT compression systems MSE should be used instead of $PSNR$ because of its better correlation with MOS ($PSNR$ has average correlation of 0.89 and MSE average correlation of 0.97 for both systems). For JPEG2000 and SPIHT compression systems MD, MSE, $LMSE$ and NAE measures demonstrate very good results. For JPEG compression system good results are achieved using $PSNR$, MD and $LMSE$. Again we can see that different measures are suitable for different compression systems.

In some image coding application, it is not appropriate to compute PQS because of its time expensiveness. Maximum difference (MD) has a good correlation with MOS for all tested compression techniques (average absolute values of r are 0.97 for JPEG2000, 0.98 for SPIHT and 0.9 for JPEG). So, we propose use of MD for comparison of picture quality in different compression systems because of its good correlation with MOS and computing simplicity. $LMSE$ has also good correlation with MOS for all tested compression techniques but this measure is not so simple as MD and has higher computational complexity than MD (see equations in Table 1 for MD and $LMSE$).

6 CONCLUSION

The results of an evaluation concerning the usefulness of a number of objective quality measures in image compression systems have been presented. In addition, picture quality is measured subjectively using perceived picture quality. The correlation between each objective measure and subjective measure is found. We demonstrated that for a given compression system a group of numerical objective measures could reliably be used to specify the magnitude of degradation in reconstructed images. We also demonstrated that this group of objective measures is different for different compression systems. We proved that MSE and $PSNR$, as traditionally used objective measures of picture quality, are not adequate as perceptually meaningful measures in all tested compression systems. We found out that PQS is the most correlated measure with MOS for all compression techniques. In some image compression application, it is not possible to compute PQS because of its time expensiveness. So we considered other objective measures of picture quality for each compression technique and we found that maximum difference (MD) has a good correlation with MOS for all tested compression techniques. So, we propose this very simple measure as a reference for measuring compressed picture quality across different compression systems.

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