No-reference method for image effective bandwidth estimation

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No-Reference Method for Image Effective Bandwidth Estimation

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ABSTRACT

Image evaluation and quality measurements are fundamental components in all image processing applications and techniques. Recently, a no-reference perceptual blur metrics (PBM) was suggested for numerical evaluation of blur effects. The method is based on computing the intensity variations between neighboring pixels of the input image before and after low-pass filtering. The method was proved to demonstrate a very good correlation between the quantitative measure it provides and visual evaluation of perceptual image quality. However, this quantitative image blurriness measure has no intuitive meaning and has no association with conventionally accepted imaging system design parameters such as, for instance, image bandwidth.

In this paper, we suggest an extended modification of this PBM-method that provides such a direct association and allows evaluation image in terms of the image efficient bandwidth. To this end we apply the PBM-method to a series of test pseudo-random images with uniform spectrum of different spread within the image base-band defined by the image sampling rate and map the image blur measurement results obtained for this set of test images to corresponding measures of their bandwidths. In this way we obtain a new image feature, which provides evaluation of image in terms of the image effective bandwidth measured in fractions, from 0 to 1, of the image base-band. In addition, we also show that the effective bandwidth measure provides a good estimation for the potential JPEG encoder compression rate, which allows one to choose the best compression quality for a requested compressed image size.

Keywords: Image Quality assessment, No-Reference, Objective metric, effective bandwidth, JPEG, Compression-rate.

1. INTRODUCTION

Image evaluation, quality measurements and characterization are fundamental components in all image processing applications and techniques. The emergence of new technologies for displays panels, cameras and mobile devices and the growth in the number of manufacturers have emphasized the need for comparison and evaluation techniques, especially in the evolution of image restoration and compression algorithms. There are basically two classes of objective quality or distortion assessment approaches. The first are mathematically defined measures of error between the evaluated image and its ideal prototype. Typical examples of such measures are mean squared error (MSE), peak signal to noise ratio (PSNR), root mean squared error (RMSE), mean absolute error (MAE), and signal-to-noise ratio (SNR) [1,2,3]. The second class of measurement methods considers human visual system (HVS) characteristics in an attempt to incorporate perceptual quality measures [4,5,6]. The required ideal image or a model, as a reference that the evaluated image can be compared to, in many cases, is not available.

Visual quality assessment through image spectra is widely used and plays a significant role in image assessment applications [4,7,8,9]. Additionally, image acquisition systems' quality is commonly determined by the optics or detector cutoff frequencies and bandwidth. However, none of the methods suggest a quantitative scalar evaluation for the effective image bandwidth. One can not compare two acquisition devices, scanners for example, and have a scalar criterion.

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Image quality metrics that do not require a reference can be found in the literature [10,11,12]. The quality assessment is based, in those methods, on the evaluation of image edge sharpness. These metrics are sensitive to the choice of the edge detector, as well as to the presence of noise, which can mislead the edge detection. To be edge detector invariant independent from any edge detector, a method which estimates image quality through the image blur effect was suggested [13]. The method compares the variations between neighboring pixels of the image before and after low-pass filtering. High variation between the original and the blurred image means that the original image was sharp whereas a slight variation between the original and the blurred image means that the original image was already blurred. The comparison result presented in a certain normalized scale as an the perceptual blur measure (PBM) ranged from 0 to 1 is shown in Ref. [13] to very well correlate with subjective evaluation of image sharpness degradation with 0 corresponding to the lowest sharpness degradation and 1 to the highest degradation.

Joint Photographic Experts Group (JPEG) is currently a worldwide standard for compression of digital images. JPEG standard uses a special quality parameter Q, which allows governing the output image quality and image compression rate. Higher Q values correspond to higher image quality, lower data loss and lower compression-rates [14,15], The compression-rate is usually defined as:

$$Compression\,Rate = \left(\frac{Raw\,Data\,File\,Size}{JPEG\,File\,Size} \right) \quad (1)$$

The JPEG File size is given in Bytes and the Raw Data File Size is the size, in Bytes, of the raw gray-level image presented on 8 bits per pixel.

In many visual transmission and storage application the desirable compressed output image size is derived from the system specifications, such as transmission-lines bandwidth and capacity of the storage device. Under those specifications, one would like to achieve the best compressed image quality. To this end, an estimation mechanism for the compressed image expected size for a predefined Q is a desirable feature. However, no such method has been suggested.

This paper presents a new image quality analysis method, derived from the PBM-method described in [13]. The method suggests a new image quality attribute, *image effective bandwidth (IEB)*, which connects the image's energy distribution in the frequency domain with perceptual image quality. The reasoning and the derivation of the effective bandwidth feature is described in Sect. 2. Sect. 3 presents the use of the IEB measure as an estimation for the JPEG standard compression capabilities. Sect. 4 proposes an analysis of the IEB and its use, as compression-rate estimator, when applied on a real-life images. Then, Sect. 5 provides the conclusion of this paper.

2. IMAGE EFFECTIVE BANDWIDTH

2.1. Generation of the Test Sets

In order to obtain numerical data that one can use to associate image bandwidth with PBM, a set of test pseudo-random images with uniform spectrum in certain fraction of the base-band was generated using a set of ideal low-pass filter masks with different circular pass bands described by the percentage α, of lower frequencies coefficients which are not filtered out (Figure 1). For example, the mask which doesn't filter any of the image frequencies corresponds to effective bandwidth of α=1. The masks which filter out half and quarter of the higher-frequency coefficients correspond to α=0.5 and α=0.75 effective bandwidths respectively. This set of filters is applied to a pseudo-random delta-correlated synthetic image. This image is referred to as the set's seed-image. In order to avoid boundary effects characteristic for Discrete Fourier Transform (DFT) we use filtering in Discrete Cosine Transform (DCT) domain. The output is a set of images, which are the seed image with uniform spectrum after filtering it with the different masks:

$$F_{test}(\alpha) = IDCT\left\{ \frac{DCT\{I_{seed}\}}{\left|DCT\{I_{seed}\}\right|} \cdot LPF\ Mask(\alpha) \right\} \quad (2)$$

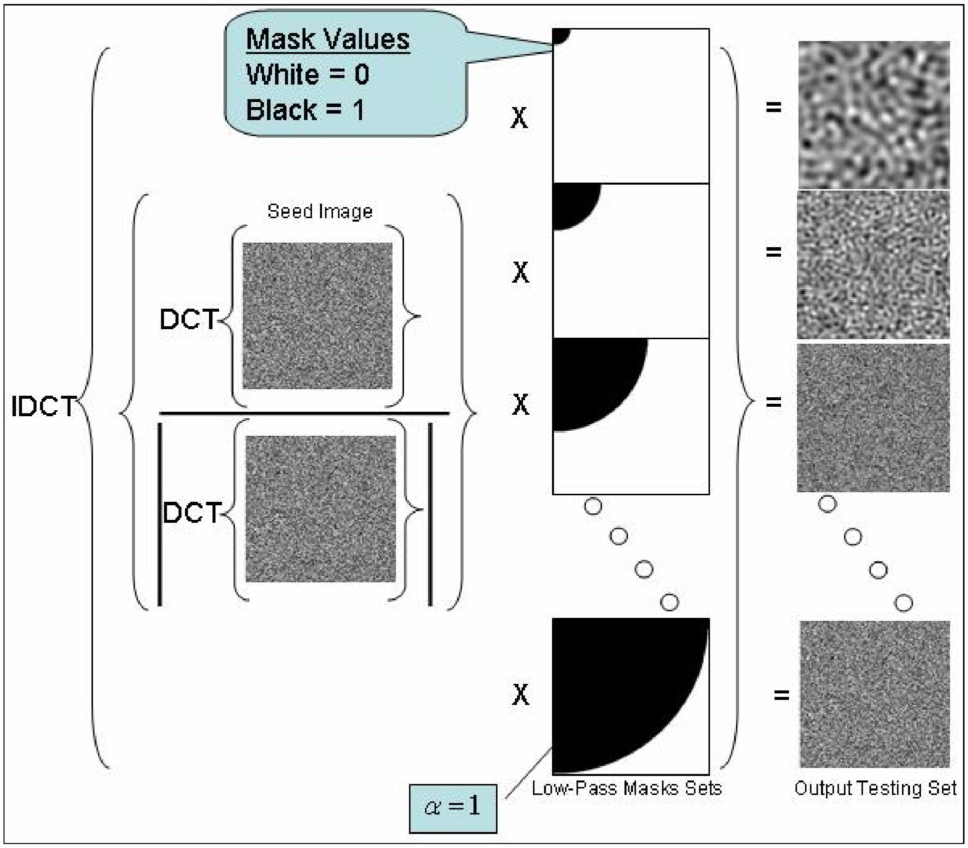

Figure 1 – The generation of the test images with known bandwidths.

2.2. Image Effective Bandwidth Formulation

For associating the PBM with the IEB measure given by parameter α, five test sets, each consisted of 256 images with different bandwidths, were generated using five different seed 256x256 images. Hence, for a given bandwidth, α, there were 5 different test images, one from each set. Those five images are referred to as bandwidth-group. The PBM was computed for each of the images. The PBM average of each bandwidth-group is depicted in Figure 2. In our tests the average PBM standard deviation for the five testing sets is 0.0006. For a larger number of test sets the standard deviation practically converges to zero. As one can see, the function described in Figure 2 is a monotonic one, which implies a direct association of effective bandwidth with a specific PBM value. The inverse relation can be used for estimation of image's effective bandwidth from its PBM. A complete Matlab software package that computes image's PBM and corresponding effective bandwidth can be downloaded from [16].

The PBM computation process is based on local features of the image. This means that the size of the image has no effect on the PBM. Figure 3 shows the PBM computation for two test sets. The first set, is one of the five sets used to generate Figure 2 and it consists of 256x256 images with different 256 bandwidths. The second set consists of 512x512 images with 512 different bandwidths. As the effective bandwidth is normalized to the image base-band, both data sets can be put on the same graph, which is presented in Figure 3, where, for better presentation, the $PBM^{0.7}$ as a function of the effective bandwidth is shown for the 256x256 (solid) and 512x512 (dashed) test sets. Since the difference is barely noticeable, a fragment of the graph is magnified. The average difference, in our tests, was 0.0007. This implies that the IEB measure is universal and can be used to compare effective bandwidths of images with different sizes.

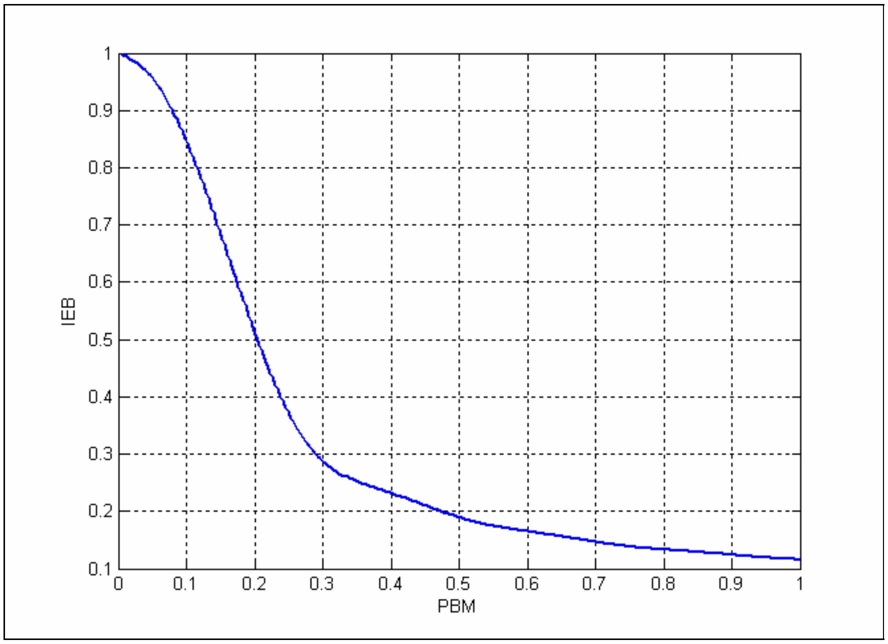

Figure 2 – The Average of the PBM computed for five test sets with known IEB

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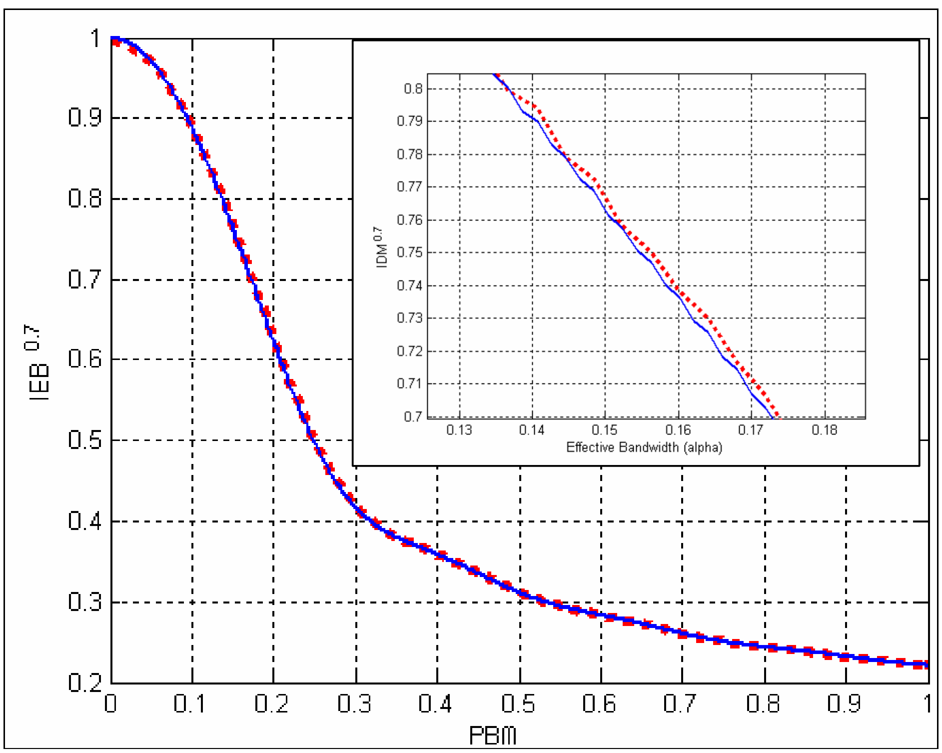


Figure 3 – The PBM computed for two test sets. The PBM of 256x256 pixels images is shown in solid line, while the PBM as a function of the effective bandwidth of the 512x512 test set is presented in dashed line.

3. JPEG COMPRESSION ESTIMATION

JPEG files are encoded by using a lossy compression adjustable with a certain quality parameter ***Q***. The lower the Q value is the smaller is the file size and heavier are image distortions. In practice, compression with Q values parameter larger than 50 are normally used. Therefore the discussion in this paper is limited for Q values larger than 40.

For a given output compressed image size, one might want to get an estimation of the amount of data to be discarded, or, in JPEG standard's terms, what Q value to be used in the compression process. The JPEG compression method utilizes, in the encoding process, spectral properties of images. This indicates that the image effective bandwidth measure introduced in Sect. 2 might be a suitable JPEG compression-rate estimator. For finding the correlation between the compression-rate and the image's effective bandwidth the test sets described in Sect. 2, consisted of random images of 256x256 pixels with 256 different effective bandwidths were used. Figure 4 presents the JPEG standard compression-rate as a function of the image's effective bandwidth for 6 different ***Q*** values (40, 50, 60, 70, 80 and 90). The graph suggests that the compression-rate, for a given ***Q*** value corresponds to a specific IEB, hence, the image's effective bandwidth can be used to estimate its potential JPEG compression-rate for a given Q.

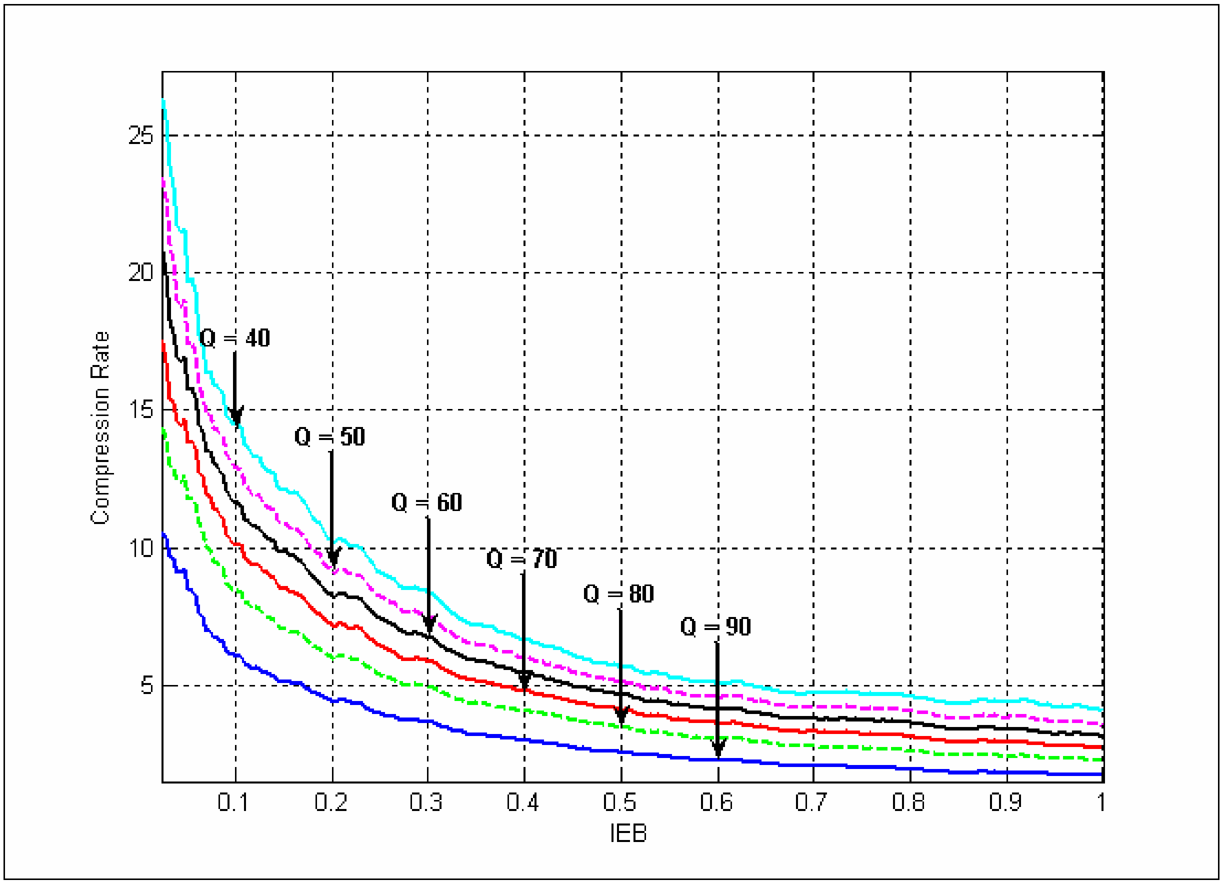
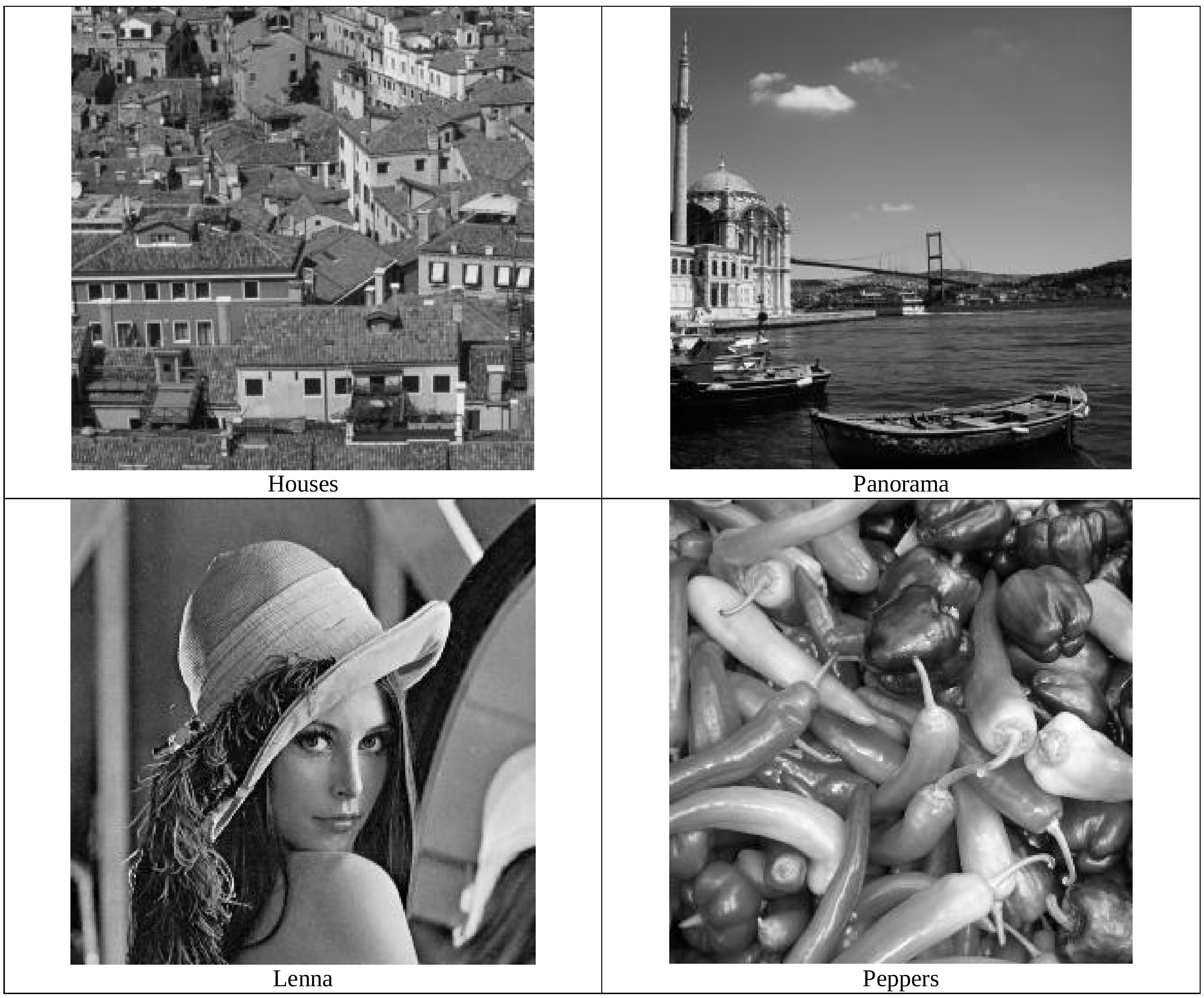


Figure 4 – JPG compression-rate as a function of the Image's effective bandwidth for five Q values (as marked on the figure) - 40, 50, 60, 70, 80 and 90.

4. RESULTS AND DISCUSSION

4.1. Effective Bandwidth

For validating the effective bandwidth measure, the four real-life images, presented in Figure 5, were used. The PBM and the effective bandwidth, for each image, are given in Table 1, which suggests that the houses image have the widest effective bandwidth, the panorama image has an intermediate bandwidth followed by the Lenna and the Peppers image which has the narrowest bandwidth of the four. This is supported by Figure 6, where the energy of the row-wise DCT coefficients normalized to the image total energy for the four real-life test images is depicted. In all graph the arrows point the corresponding image's IEB. As one can see higher IEB measures do correspond to larger portion of the image energy in its higher frequencies. This is presented quantitatively in Table 2, where the total energy portions sited in the higher half of the DCT base-band as well as the portion of the energy from the images' IEB onwards are given. Those results support the notion that the PBM measure suggested in [13] is suitable for measuring the image effective bandwidths.



Houses | Panorama | Lenna | Peppers

Figure 5 – 4 Real-life images used in the validation process: Houses, Panorama, Lenna and Peppers

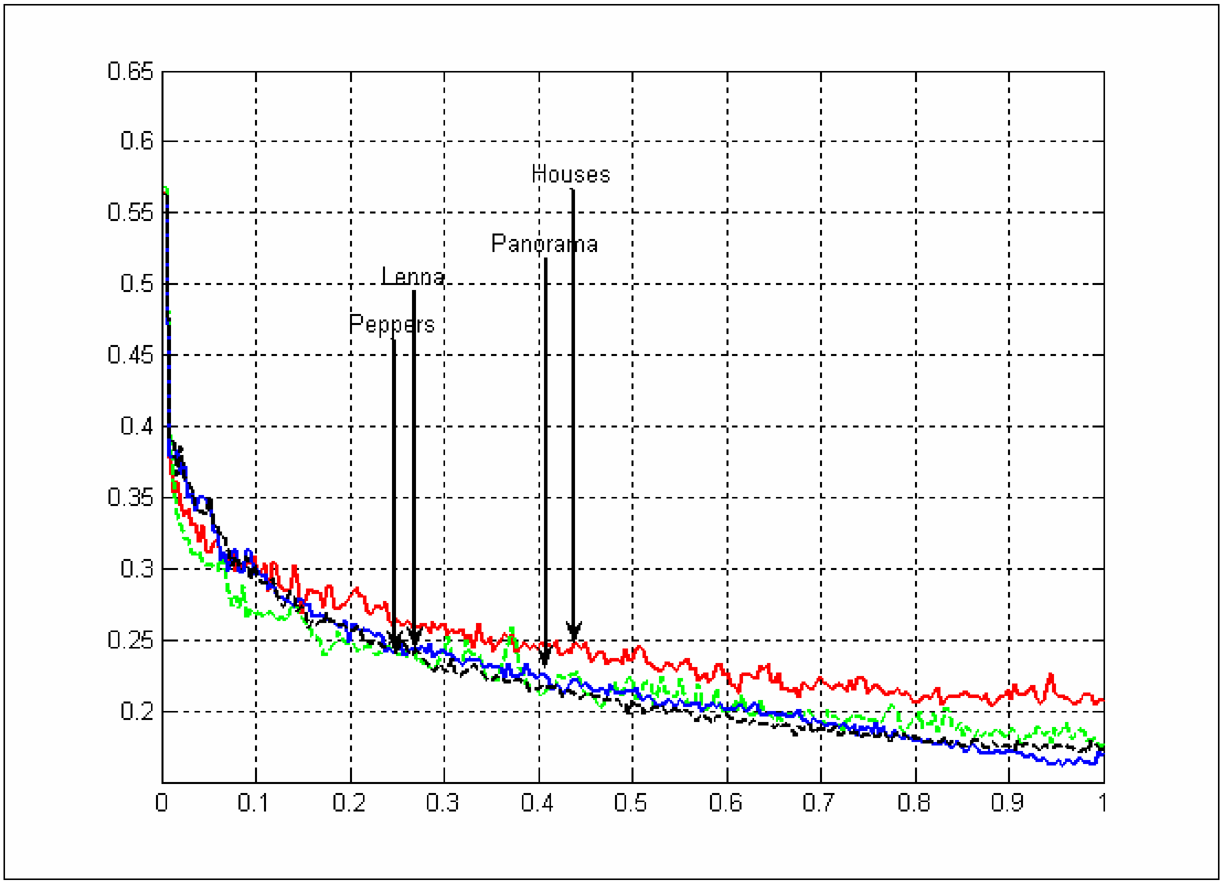


Figure 6 – energy of the row-wise DCT coefficients normalized to the image total energy for the four real-life test images. the arrows point the corresponding image's IEB.

Table 1 – Real-life images PBM and effective bandwidth measures

Image	Houses	Panorama	Lenna	Peppers
PBM	0.21	0.23	0.33	0.37
Effective Bandwidth	0.44	0.41	0.27	0.25

Table 2 –Energy of higher frequencies DCT coefficients as a fraction of the total energy of images and their effective bandwidth

Image	Houses	Panorama	Lenna	Peppers
Effective Bandwidth	0.44	0.41	0.27	0.25
Normalized energy of higher half of the DCT coefficients	0.0183	0.0102	0.0038	0.0036
Normalized energy of the higher DCT coefficients beginning from IEB	0.0231	0.0142	0.0112	0.0132

4.2. JPEG Compression Estimation

Figure 8 and Figure 9 present the JPEG compression-rate, as defined by Eq. (1), for a test set with effective bandwidths of 0.1, 0.2, 0.3, …, 0.9 while compressed with JPEG compression quality, Q, of 90 and 60respectively. On top of this graph the 23 real-life images' compression rate was placed according to their computed effective bandwidths. 19, of the 23, images are shown in Figure 7, the other 4 images are the test images used in 4.1 and are given in Figure 5. As one can see, from the graphs, the compression rate of the random images can produce a good estimation mechanism for a given image expected compression rate.

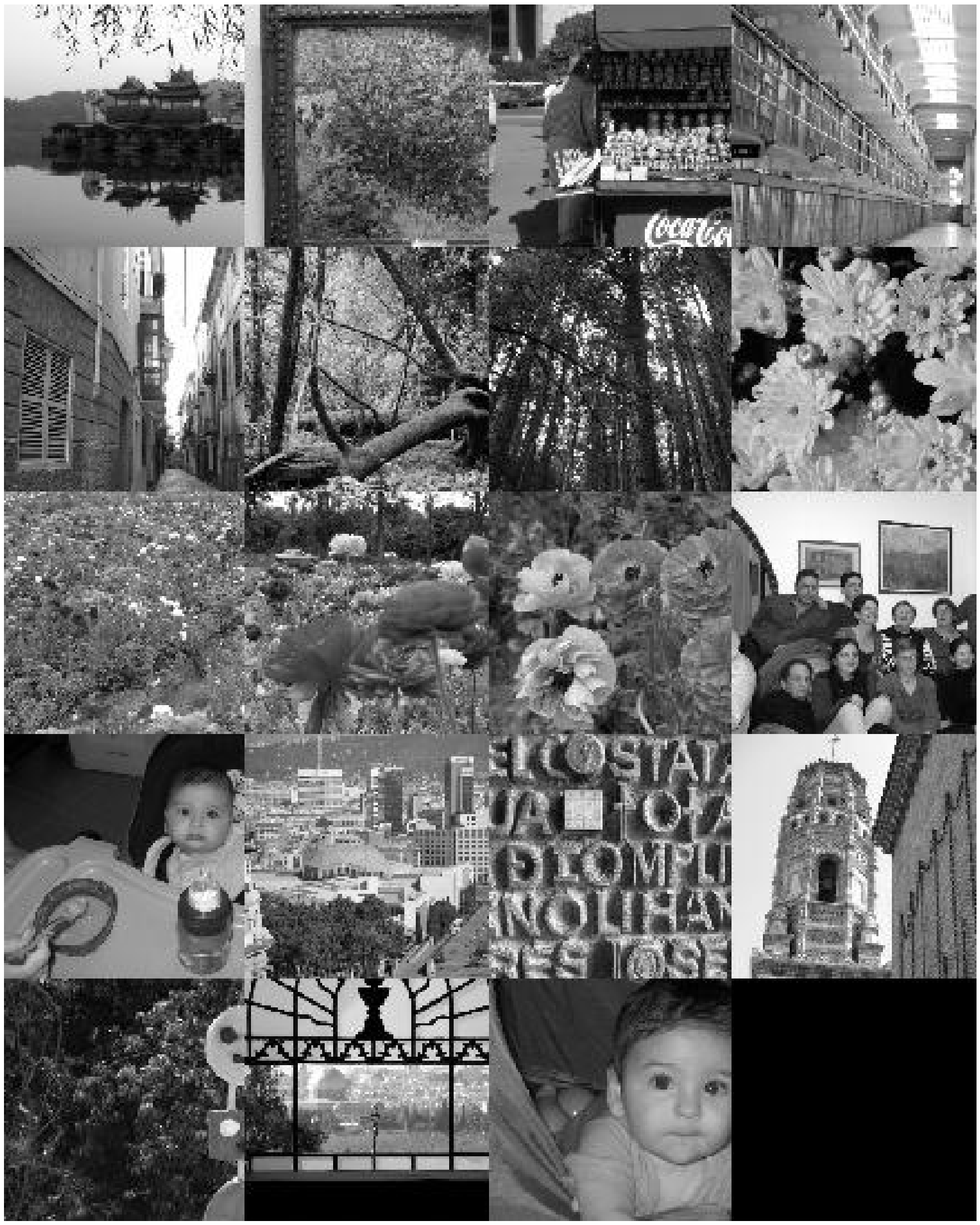


Figure 7 – Real-life images used for evaluating the validity of the IEB as a JPEG compression rate predictor.

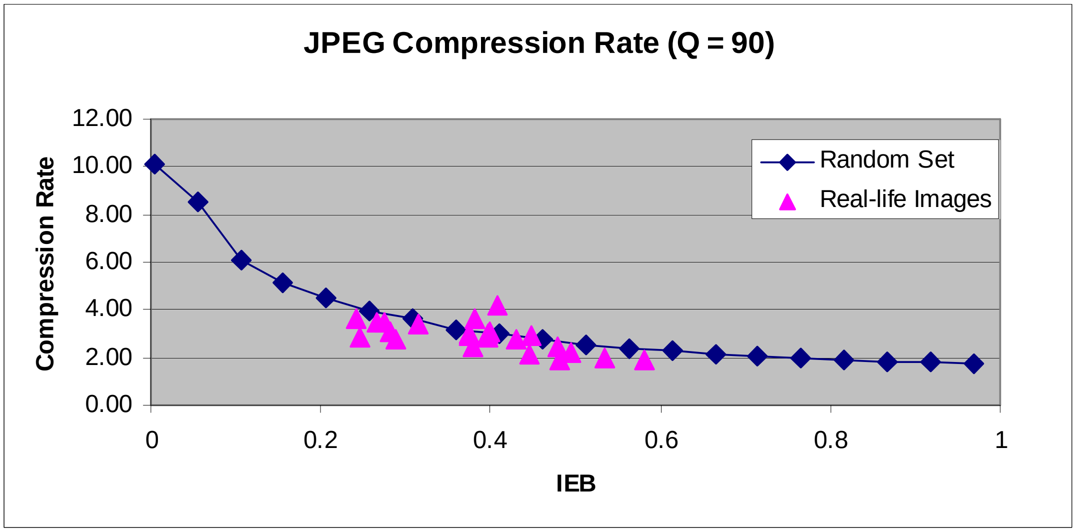


Figure 8 - JPEG compression-rate vs. the image effective bandwidth for data-loss Compression parameter equals 90. The diamonds are the compression rate for the random data tests images with known bandwidths. The compression-rate of 23 real-life test images are marked with triangle in their corresponding effective bandwidths.

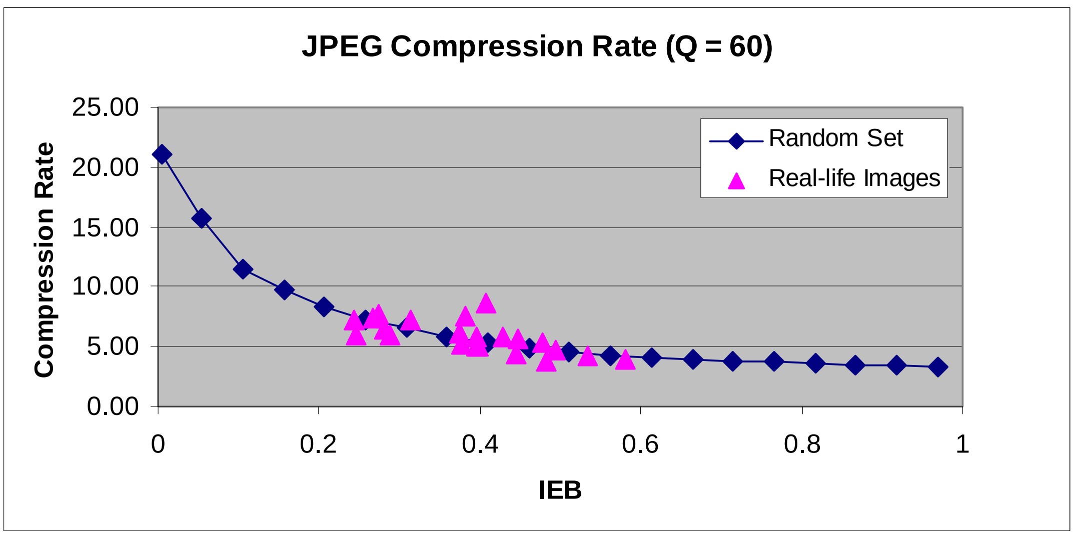


Figure 9 - JPEG compression-rate vs. the image effective bandwidth for data-loss Compression parameter equals 60. The diamonds are the compression rate for the random data tests images with known bandwidths. The compression-rate of 23 real-life test images are marked with triangle in their corresponding effective bandwidths.

5. CONCLUSION

This paper suggests *effective bandwidth* as a new image feature that fits an intuitive meaning and is associated with conventionally accepted imaging system design parameters. The effective bandwidth feature is suggested also as a predictor the compressed image file size for a given Q value. This allows the user to select the best Q value for a specific transmission bandwidth or storage specifications.

Our results show that the effective bandwidth is in one-to-one correspondence with subjective evaluation of image sharpness and can be used as a good indication for image energy distribution in higher frequencies of the image base-band. The effective bandwidth parameter was formulized using synthetic test sets of random images with known bandwidths and the obtained results of the synthetic set have shown their validity when applied on real-life images. Additionally the suggested IEB has shown great potential as a predictor of the JPEG compression rate. A further investigation of the compression rate vs. IEB will allow forming a consolidated framework for evaluating image JPEG compressibility. This mechanism might become useful where the compressed output image size is derived from the system specifications and one would like to achieve the best compressed image quality under those requirements.

A Matlab software package for computing images effective bandwidth is offered on the author's site. The package will allow one to evaluate images' IEB and to compare them with the synthetic test images, with known bandwidth, which are part of the software package.

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