Structural Similarity Image Quality reliability. Determining parameters and window size.

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Abstract

The need to obtain objective values of the quality of distorted images with respect to the original is fundamental in multimedia and image processing applications. It is generally required that this value correlates well with the human vision system (HVS). In spite of the properties and the general use of the Mean Square Error (MSE) measurement, this has a poor correlation with HSV, which has led to the development of methods such as Structural Similarity (SSIM). This metric improves the correlation with respect to the classic MSE and PSNR (Peal Signal to Noise Ratio). However, its behavior depends on the values assigned to constants and in the windows size selected. These values are usually assigned arbitrarily and there have been no studies on how they affect the SSIM. In this work, we have analyzed empirically the most appropriate values for the different constants used in the SSIM equations. We have also analyzed the importance of window size in the calculation of MSSIM, and propose a method for determining the window size based on image complexity. Using the values selected and the window size defined, the correlation between SSIM and DMOS is significantly improved

by around 17% with respect to the values commonly used.

Keywords: Image quality assesment, structural similarity

1. Introduction and related work

The significant growth in the development and use of multimedia technology in a wide range of fields has led to a rapid expansion in its use. In many of the applications their behavior depends on the quality of the input images. Degradation in quality has a negative effect on user perception or on the image processing algorithm that makes use of this to take measurements and draw conclusions (see Fig. 1).This means that it is necessary to develop methods that allow efficient evaluation of this quality.

Evaluating the signal received at the application destination ($\boldsymbol{g}$) with respect to the original signal ($\boldsymbol{f}$) can be carried out without knowing f (NR: no reference. [1]), knowing some properties of the original signal (RR: reduced reference. [2][3][4]), or knowing f completely (FR: Full reference.[5]).

In the last case, subjective evaluation and the corresponding Difference Mean Opinion Score (DMOS) is the most accurate method to get close to the HVS (Human Visual System), although it does have certain disadvantages; mainly that it is slow, costly and cannot be used in real time. Objective evaluation, that is to say, the development of formulas which allow us to predict the quality perceived by HVS, or its influence on the image processing algorithms, are a widely sought solution. For many years, MSE has been used as a measurement, in spite of the drawbacks associated with it [6], especially its poor correlation with HVS. In the image processing for industrial and robotics area, this connection has also been researched, and the drawbacks with classic metrics have been demonstrated in practical cases [7][8]. Recently, measurements have been developed that are not based on measuring the error, but instead evaluate structural similarity [9][10] (SSIM) and these have shown a stronger correlation with HVS, and are currently used in a wide range of multimedia applications. However, this method still has certain limitations, which have led to the development of new measurements based on the same method. In [11], an SSIM is presented in which the original parameter for evaluation of the structure (s) in the SSIM equation is substituted by an *s'* dependent on the edges. In [12] the authors analyze how perceived quality depends on local characteristics such as edges, texture and flat areas. A metric is proposed which consists of evaluating the similarity between edges and contrast. In [13] there is an analysis of the SSIM measurement's performance, comparing this with traditional approaches with realistic distortions, highlighting the need for a Perceptual weighting for distortions that are critically dependent on viewing distance. In [14] an analysis to simplify the calculation is performed. In [15] the authors propose a method based on SSIM, where different areas (textures, edges and smoothed regions) are extracted and the weight that each should have in the final measurements is analyzed In [16] SSIM is improved by weighting the quality measurements with visual importance. Other proposals analyze their use for range images [17], or the improvement obtained through image definition [18].

In this paper, we analyze the influence of the constants on the calculation of the SSIM and whether a better selection of these constants can offer some improvements to SSIM. Another parameter that has not been studied in sufficient detail is window size. In this paper, we study this parameter,

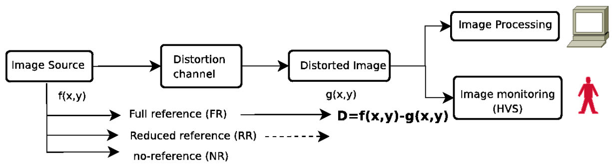

Figure 1: General multimedia application *diagram*

showing how it can significantly alter the SSIM values. We later propose an objective method that will allow us to define a concrete window size for each image, thus eliminating the subjectivity with which this value is generally selected.

The remainder of this paper is organized as follows. In section 2, there is an introduction to SSIM, including an analysis of the incidence of constants and windows size. In section 3, we present a method for determining window size (B) for MSSIM calculation. In section 4, an empirical analysis of the constant values is performed, and we describe and compare the correlation between the MSSIM values obtained through the determination method proposed in B and the use of **constants values**, and finally, we draw our conclusions at the end of the final section.

2. Structural Similarity (SSIM)

2.1. How structural similarity can be calculated

Structural similarity can be obtained by comparing local patterns of pixel intensities that have been normalized for luminance and contrast. This measurement is based on the fact that the structures of the objects in the scene are independent of illumination, so the influence of illumination must be isolated. Luminance ($\boldsymbol{l}$), contrast ($\boldsymbol{c}$) and structure ($\boldsymbol{s}$) are independently measured in this method. The mean intensity of the distorted image (μ_g) and the reference image (μ_f) have to be calculated for a comparison of luminance. Thus, if M and N are the width and height of image, the mean of each one (replace i with f or g) can be measured as:

$$\mu_i = \frac{1}{NM} \sum_{x=1}^{M} \sum_{y=1}^{N} i(x, y) \tag{1}$$

The standard deviation of distorted image (σ_g) and reference image (σ_f) is used as a measurement of the contrast of the signal. Thus, for each image it can be calculated as:

$$\sigma_i = \sqrt{\frac{1}{NM - 1} \sum_{x=1}^{M} \sum_{y=1}^{N} i(x, y) - \mu_i} \tag{2}$$

The measurements of the structure are based on the normalized signals (e.g. $i(x, y) - \mu_i/\sigma_i$) in such a way that both have a standard deviation of 1. In this way we obtain:

$$\mathbf{l(f,g)} = \frac{2\mu_f\mu_g + C_1}{\mu_f^2 + \mu_g^2 + C_1} : \mathbf{c(f,g)} = \frac{2\sigma_f\sigma_g + C_2}{\sigma_f^2 + \sigma_y^2 + C_2} \tag{3}$$

$$\mathbf{s(f,g)} = \frac{\sigma_{fg} + C_3}{\sigma_f\sigma_g + C_3} \tag{4}$$

If σ_{fg} is the covariance between the signals f and g, and C_i is included to avoid instability in the measurements, SSIM can be calculated as follows:

$$SSIM(f, g) = (l(f, g))^{\alpha}(c(x, y))^{\beta}(s(f, g))^{\gamma} \tag{5}$$

When the constants defined in [10] are used, as well as $\alpha = \beta = \gamma = 1$, then the following aproximation is used:

$$SSIM(f,g) = \frac{(2\mu_f\mu_g + C_1)(2\sigma_{fg} + C_2)}{(\mu_f^2 + \mu_g^2 + C1)(\sigma_f^2 + \sigma_g^2 + C_2)} \tag{6}$$

The results from using this method are more useful if they are applied locally instead of globally [10], so the preceding formulas, instead of being applied over the complete image, are applied over windows of size BxB pixels which are displaced pixel by pixel in the image ($SSIM^B$). Thus, if T =(M - 1)(N - 1), the value of MSSIM is calculated as the average of the values obtained in each window:

$$MSSIM^B(f,g) = \frac{1}{T}\sum_{i=1}^{T} SSIM_i^B \tag{7}$$

2.2. SSIM variability

Although SSIM has proven to perform quite well, has good correlation with HVS, and is quite widely used, there are some drawbacks with this measurement. The most relevant of these is that the values obtained are very dependent on certain of their parameters. Figure 2 shows three images that are commonly used for image quality evaluation: lena, goldhill and couple. In [9] (the original images and the distorted versions can be obtained in http://www.cns.nyu.edu/s̃wang/ files/research/ quality_index/ demo.html) the following distortions are applied: 1) Impulsive Salt-Pepper Noise, 2) Additive Gaussian Noise, 3) Multiplicative Speckle Noise, 4) Mean Shif,t 5) Contrast Stretching, 6) Blurring and 7) JPEG Compression, to produce a distorted image with MSE of 255, 125 and 81 over lena, goldhill and couple respectively. We then show how distorted images with the same MSE have different SSIM values, and how these values have a better correlation with HVS.

The constants C1, C2 and L are calculated as [10]:

$$C1 = K_1 L^2; C2 = K_2 L^2 : C3 = C2/2 \tag{8}$$

generally using the values of K1=0,01, K2=0,03 and L=255 [10][16]. Table 1 shows the combination values used in this paper, while S_5 is the set of values normally used. The choice of these constants, introduced to avoid instability when the denominators were too small, could have a considerable effect on the performance of the system. Figure 3 shows the influence this value has on $MSSIM^7$, that is to say, using a window B=7, and with the constants shown in Table 1. Thus for the most distorted image, and for the distortions with greater visual incidence (D6 and D7), there are differences of 0.5 MSSIM points between using one set of constants or another (Fig. 3.a), while these differences are of 0.3 and 0.2 in images with lesser distortions (Fig. 3.b and 3.c). With the exception of the distortions with low incidence on the SSIM value (D4 and D5), in the rest the effect of this parameter is clearly appreciable.

Although there is no information available to analyze the correlation between these values and the DMOS, it is evident that this variability affects the order of worst to best. For example, according to Fig. 3.a, for S_1 we would obtain (D7,D6,D2,D3,D1,D5,D4), while for S_6 the order would be (D2,D3,D6,D7,D1,D5,D4).

With respect to the window value B, if this information is provided, which size of window (B) is used and why? In [9] and [11] B=8 is used, whereas B=7 in [13] and they also define a range between 7 and 15 for 512x512 images as the correct choice. In [17][15] B=11 is used, and also in [9][16]

Table 1: Constant Set S

	K1	**K2**	**C1**	**C2**
S_1	0,00004	0,00012	0,0001040	0,0009364
S_2	0,0025	0,0075	0,406406	3,6576
S_3	0,0050	0,015	1,625	14,630
S_4	0,0075	0,022	3,657	32,918
S_5	**0,01**	**0,03**	**6,50**	**58,52**
S_6	0.02	0.06	26,01	234,09

although combined with a circular-symmetric Gaussian weighting function for a better SSIM map visualization. The significance of B in the MSSIM values obtained can be seen in Fig. 4, where constants are S_1. For the most relevant distortions for HVS, we can obtain differences of around 0.5 in the MSSIM for slightly distorted images (Fig. 4.c), and up to 0.7 for more distorted images (Fig. 4.a) in the MSSIM obtained with different Bs. Limiting the range of B to the most commonly used values, between 7 and 15, significant variations are also produced (up to 0.2 points above the MSSIM value obtained). This variability could modify the order that this metric provides with respect to the distortions depending on the window size used. Thus, in Fig. 4.a for B=3 we would obtain (D7,D6,D2,D3,D1,D5,D4), while for B=31, this order would be (D7,D1,D2,D3,D6,D5,D4).

The variability in the MSSIM value obtained according to the S and B values used could be unacceptable for some applications. Therefore an analysis is necessary to determine which values are most appropriate, and methods must be developed to determine the value of B with the aim of reducing the variability in the measurements and improving the correlation with HVS.

3. B size definition

The choice of the most appropriate set of constants is done experimentally analyzing the correlation obtained between the MSSIM values obtained and the DMOS values from a collection of known data. Concerning the choice of B value, analyzing different images and the results obtained through MSSIM using different B values, one can intuitively appreciate a relationship between the most appropriate B size and the complexity of the image. Therefore, if Ψ is the complexity of the image, the objective would be to find the function $\mathcal{F}$, so that:

$$B = \mathcal{F}(\Psi)/MSSIM^{B}(f, g) \Rightarrow DMOS(f, g) \tag{9}$$

Although there are more advanced methodologies in existence to determine Ψ (see [19]), the entropy of the gray level histogram [20] is widely used. If n is the number of gray levels and p_i the frequency of gray level i in an image f, this can be calculated as:

$$H(f) = -\sum_{i=0}^{n} p_i log_2 p_i \tag{10}$$

However, this measurement does not take into account the spatial distribution of pixels, which intuitively is quite relevant for image complexity. It is well know that a part of the complexity of an image comes from the collection of edges that the image contains. Thus, instead of applying the entropy calculation to the original image f, it is applied to the image after application of a Sobel filter, and we thus obtain $H'(sobel(f))$.

In Fig. 5 we can see the H and H' values obtained for the set of 29 images used in the next section. Although there is an apparent relationship between H and H', H' clearly identifies more accurately the differences between images with a different complexity. This can be clearly seen in Fig. 6.a, which shows the original images of carnival dolls and cemetery together with the same images, converted to greyscale and after application of a Sobel filter (we show inverted Sobel for better visualization). These images have a very different level of complexity (there is a great deal of uniform background in the first image), but they give a similar value of H, and so H' is more appropriate to highlight the difference. On the other hand, other images with similar complexity (for example parrots and aeroplane in Fig. 6.b) produces quite different H values, which are only correctly reflected using H'.

F has been obtained empirically through the analysis of the relation between DMOS and SSIM for different B values, resulting in:

$$B = -22.77 log(H') + 45.47 \tag{11}$$

which is rounded to the higher natural number.

4. Experiments and Results

A classic study is to apply different types of distortions and then evaluate which measurements have a better correlation with the HVS. For the evaluation of the $MSSIM^B$ results obtained for B connected with image complexity and the empirical analysis of S the *Live Image Quality Assess Database Release 2* is used [21] (http://live.ece.utexas.edu/ research/ quality). This is the large collection of distorted images with subjective visual quality ratings available, used in the most recent studies on image quality [14][16][15]. From the 29 images studied, different levels and types of distortion are generated, giving 227 JP2k images, 233 JPEG, 174 with white noise (WN) and 174 gaussian blur (GB) above the known values of DMOS, giving a total of 982 images. The tools developed for this paper can be obtained at http://muro1.alc.upv.es/ sp/ bsizedet.html). The correctness of the implementation is validated through the SSIM values ($B = 8$ and S_0) obtained for the distortions and images [9] presented in section 2.2.

The $MSSIM^B$ values were calculated for various values of B and S, being $B = F$ the value of B depending on entropy and on equation 11. We analyzed the linear Pearson correlation coefficient (CC) that exists between the $MSSIM^B$ values obtained [21] and the DMOS. The closer this is to -1, the stronger the correlation between the values obtained, such as MSSIM and the corresponding values of DMOS, and therefore, the MSSIM values correspond better with the HVS (in the graphics, CC is inverted for better visualization, and 1 is the value that represents the best visualization). The CC values obtained for the conventional methods are presented in Table 2.

Fig. 7 shows the scatter plots of DMOS and $SSIM^B$ for four B values and two S_i values, using S_1 for the left column and S_5 for the right, and changing B from up to down in F, 7, 15 and 30. We can see how for S_1 as well as for S_5, on increasing the size of B the points move to the right, that is to say toward higher $MSSIM^B$ values, reducing the correlation between this value and the DMOS. In this figure, we can also see how for the same value of B, a similar effect is produced as the value of S_i increases, reducing the correlation as the constant values increase.

Table 2: Correlation Coefficient for classical metrics

	JPEG	GB	JP2K	WN	ALL
MSE	0.691	0.705	0.704	0.835	0.405
PSNR	-0.840	-0.774	-0.875	-0.979	-0,78

An analysis that is specific to each type of distortion is shown in Fig. 8, where the CC values for each type of distortion are shown according to the window size analyzed, from 3 to 30, and for different values of S_i. Table 3 shows some of these values, including in column B=F the CC obtained using a variable window size according to equation 11, and the maximum CC value is marked in bold. We can see that for the JPEG and JP2K distortions, smaller window sizes give better correlation in general, *and this size is lower when when the constants used are lower.* Thus, for JPEG and S_1 the best B is 3, but for S_2 and S_3 B=5 is better and for S_5 and S_6 B=7 is the best while for JP2K B=5 is the best size for all S_i except for S_6, where it is improved with B=7. For the Gaussian Blur distortion, the optimum B values are between 7 for the collection of smallest constants, and 11 for the largest. For white noise, the correlation increases alongside an increase in the size of B, and this difference diminishes as we increase the value of the constants used, until we reach S_6 at which point the trend is reversed.

Concerning the optimum value of S_i, for the GB distortion, CC improves as the constants are lowered, and S_2 is the point at which we obtain the best CC values CC. For the JPEG and JP2K distortions, there was no clear trend independent of the value of B, and the the highest values were obtained with

S_3 in the case of JP2k and S_1 for JPEG. For WN, the higher the constants, the better the values of CC obtained.

Therefore, there is not a constant B and S_i that allows us to obtain the best correlation with all the different types of distortion. The use of small constants S_i and of a size of B dependent on image complexity gives the best global CC, as can be seen in table 3 and in Fig. 9, and the correlation improves with respect to PSNR for all distortions (10.8% in JPEG, 23.5% in GB and 7% in JP2K) except for WN (where it worsens by 5%). Comparing the proposed method (using S_1 and B depending on image complexity) with the most common S_5 and B=11, we obtain a global improvement of 17.3%. Table 4 shows the values obtained for the EMSSIM according to [11]. As can be seen, the correlation with this metric is also improved by adapting the window size depending on the function $\mathcal{F}$ proposed, and using the smallest constant values, in particular those of S_1.

5. Conclusions

The use of MSSIM offers significant advantages with respect to MSE. However, the SSIM values obtained are extremely dependent on the values of B and S used, and can give significant differences depending on the value chosen. Normally, a value of B around 8 is selected, or a constant in the range [7,16], and S_5 is selected as a constant set. We have also shown how this can produce differences in the SSIM obtained of up to 20%, which is not really acceptable as a precise measure of quality. In this paper, we have empirically selected a set of constants with a better correlation with HVS. We also propose a variable B value which is a function of image complexity

Ψ, as well as the function $\digamma$ itself to obtain this value of B, which improves the correlation between SSIM and DMOS with respect to the best case using a constant B. Moreover, the method improves other metrics based on SSIM, like EMSSIM, which lead us to conclude that this can be applied to other proposals being carried out. Future work will be to improve Ψ and $\digamma$, and also to analyze the use of this choice of B in other measurement proposals based on structural similarity.

6. Acknowledgements

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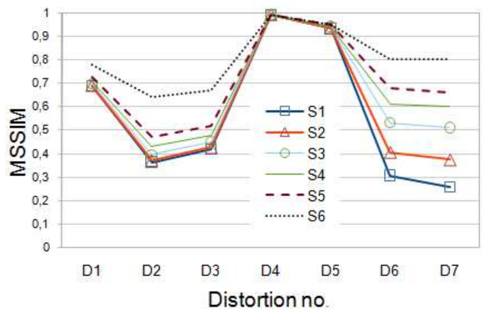
a) Lena

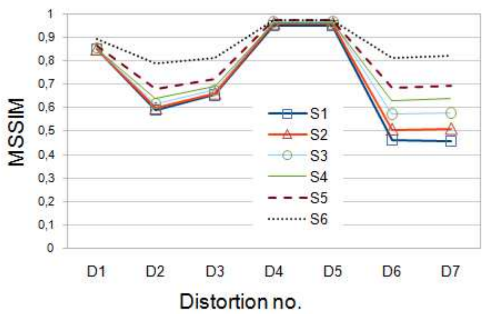
b) Goldhill

c) Couple

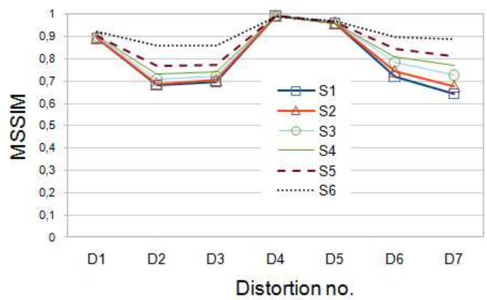
Figure 2: Classic images used for quality evaluation



a) Lena. MSE=255

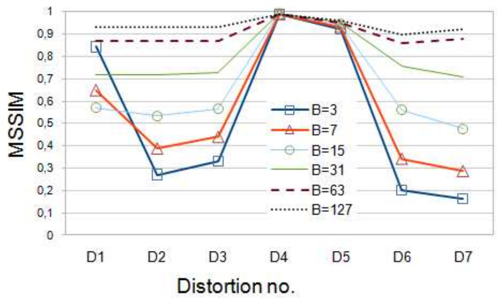


b) Goldhill. MSE=125

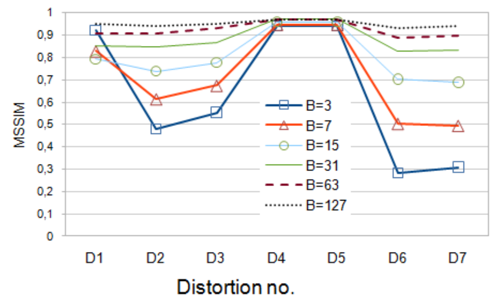


c) Couple. MSE=81

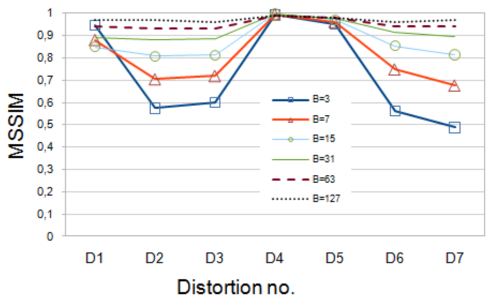
Figure 3: SSIM indeces variation depending on S_i with B=7



a) Lena. MSE=255



b) Goldhill. MSE=125



c) Couple. MSE=81

Figure 4: SSIM indeces variation depending on B with S_1

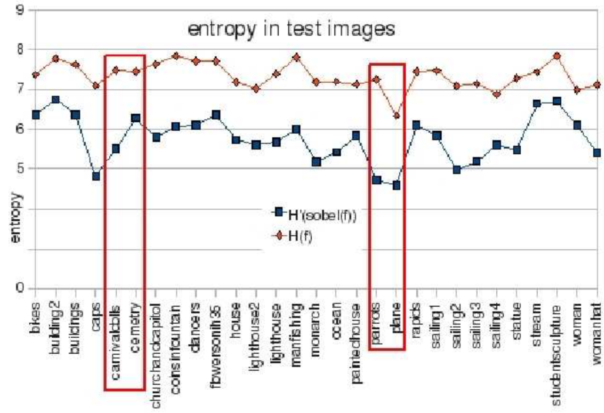
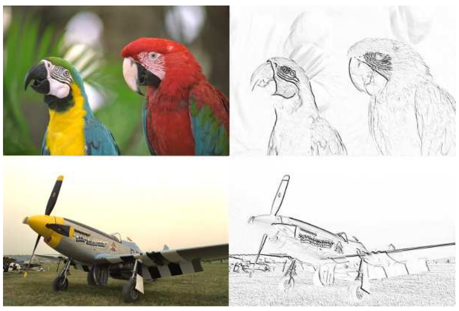


Figure 5: H and H' values obtained

a)carnival dolls and cemetery



b) Parrot and aeroplane

Figure 6: f and f(sobel)

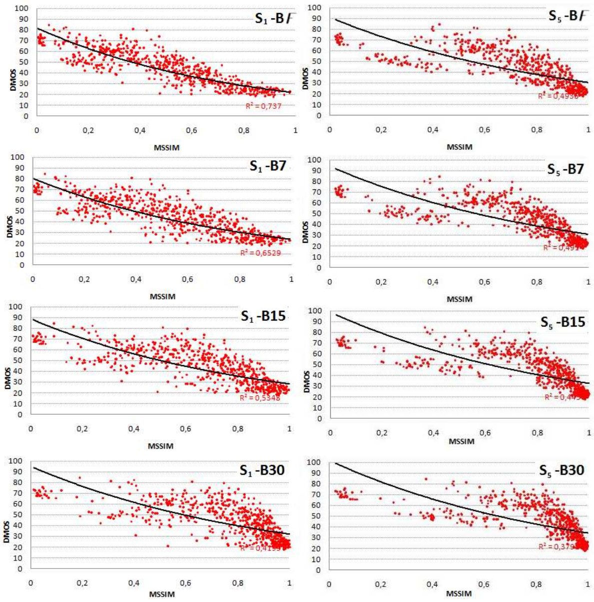
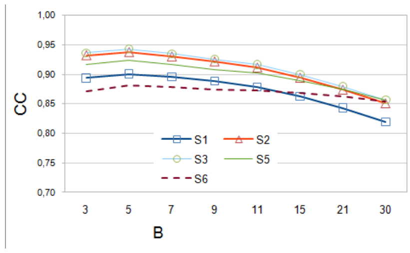
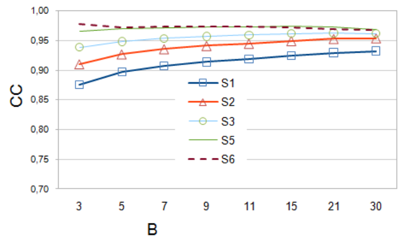


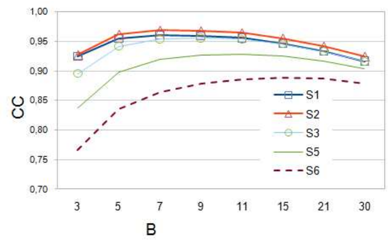
Figure 7: Scatter plot of DMOS and MSSIM



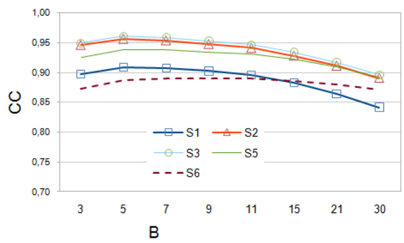
a) JPEG



b) WN



c) GB



d) JP2K

Figure 8: CC indeces variation depending on B for different S

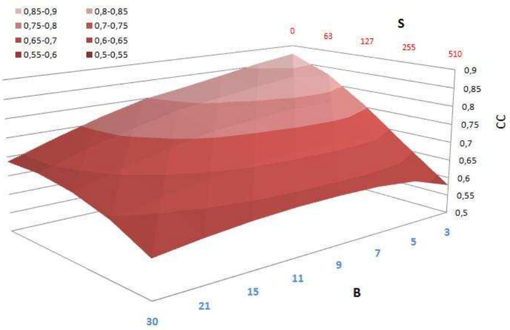


Figure 9: Global CC indeces variation

Table 3: CC MSSIM and DMOS

JPG	B=F	B=3	B=5	B=7	B=11	B=30
S1	0.931	**0.953**	0.931	0.913	0.883	0.801
S2	0.936	0.932	0.937	0.930	0.911	0.850
S3	0.926	0.936	0.943	0.935	0.916	0.856
S5	0.903	0.916	0.924	0.917	0.902	0.856
S6	0.868	0.870	0.881	0.879	0.872	0.853
GB	B=F	B=3	B=5	B=7	B=11	B=30
S1	0.956	0.924	0.955	0.960	0.955	0.916
S2	0.936	0.927	0.961	**0.968**	0.964	0.924
S3	0.912	0.895	0.942	0.954	0.953	0.916
S5	0.880	0.837	0.898	0.919	0.928	0.903
S6	0.841	0.765	0.834	0.864	0.885	0.879
JP2K	B=F	B=3	B=5	B=7	B=11	B=30
S1	0.940	0.897	0.909	0.907	0.896	0.841
S2	0.952	0.946	0.956	0.954	0.941	0.890
S3	0.943	0.949	**0.960**	0.958	0.946	0.896
S5	0.921	0.925	0.938	0.938	0.930	0.892
S6	0.881	0.872	0.887	0.890	0.889	0.871
WN	B=F	B=3	B=5	B=7	B=11	B=30
S1	0.931	0.875	0.897	0.907	0.910	0.932
S2	0.947	0.910	0.927	0.935	0.928	0.954
S3	0.961	0.938	0.948	0.954	0.946	0.962
S5	0.974	0.965	0.969	0.971	0.964	0.969
S6	**0.979**	0.978	0.973	0.973	0.973	0.967
ALL	B=F	B=3	B=5	B=7	B=11	B=30
S1	**0.905**	0.881	0.887	0.879	0.854	0.753
S2	0.881	0.875	0.880	0.871	0.845	0.749
S3	0.847	0.838	0.848	0.842	0.819	0.734
S5	0.788	0.768	0.787	0.786	0.771	0.705
S6	0.702	0.674	0.697	0.701	0.696	0.655

Table 4: CC EMSSIM and DMOS

ALL	B=F	B=3	B=5	B=7	B=11	B=30
S1	**0.885**	0.840	0.869	0.880	0.878	0.826
S2	0.875	0.831	0.863	0.875	0.874	0.826
S3	0.867	0.823	0.856	0.869	0.870	0.825
S5	0.858	0.815	0.847	0.862	0.864	0.823
S6	0.848	0.807	0.838	0.854	0.857	0.820