Difference of Visual Information Metric Based on Entropy of Primitive

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Abstract: Image sparse representation is a method of efficient compression and coding of image signal in the process of digital image processing. Image after sparse representation, to enhance the transmission efficiency of the image signal. Entropy of Primitive (EoP) is a statistical representation of the sparse representation of the image, which indicates the probability of each base element. Based on the EoP, this paper presents an image quality evaluation method-Difference of Visual Information Metric (DVIM). The principle of this method is to evaluate the image quality with the difference between the original image and the distorted image. The comparative experiments between DVIM & PSNR & SSIM are carried out. It was found that there was a great improvement in the image quality evaluation method, which overcomes the weakness of other quality evaluation methods for geometrically changing images to a certain extent, and is more consistent with the subjective observation of the human eye.

Keywords: Entropy of primitive, visual information, visual information difference measurement.

1 Introduction

The signals input by the computer from imaging devices such as cameras and cameras must be sampled, quantized, etc., and the analog signals are converted into digital signals for analysis and processing [Bi (2017)]. In the process of digital image transmission, the principle of RGB three primary colors is often used to represent an image. A color image of size m×n, in the memory to store a "m×n"×3 multidimensional data arrays, indicating that a pixel needs to use $3\times8=24$ bit, a frame rate of 60 fps 720p video. The data for one second is 60×2.64 MB=158.4 MB. The amount of data in digital images is huge, and images and videos must be compressed to increase efficiency. There is redundant information in the process of image compression for transmission. This information includes multiple kinds of redundancy, the most important of which are spatial redundancy, time redundancy and information entropy redundancy. By analyzing and extracting the information, removing the correlation between the image and the image, and then compressing the data, a better result

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can be achieved [Digne, Galin and Peytavie (2016)]. The compression standard adopts a compression method based on a hybrid coding framework. Common compression processing methods include: preprocessing, prediction, transform, quantization, and entropy coding. Drawbacks analysis of traditional wireless sensor network.

In the process of compression, acquisition, processing, storage, transmission, reconstruction, etc., the image is interfered by the inevitable factors such as physical principles, algorithms, resource constraints and channels, resulting in data distortion, and data loss will bring visual Degraded.

The subjective observation method using the visual perception of "human eyes" usually cannot describe and quantify the quality of images well [Hu, Wu and Lin (2014)]. Therefore, studying a quality evaluation method that can replace the subjective quality evaluation of "human eyes" can improve the efficiency of image quality evaluation, a more comprehensive evaluation of an image. This paper mainly discusses an image quality evaluation method that can automatically predict the visual quality of the image and make the prediction result close to the subjective evaluation result of the human eye.

At present, the quality evaluation methods are mainly divided into subjective quality evaluation methods and objective quality evaluation methods. The Mean Opinion Score (MOS) is to let the observer judge the quality of the test image according to the pre-specified evaluation scale and give the quality score, and then weight the average of the scores given by all the observers [Jiang and Peng (2016)]. The score is normalized, and the obtained value is the subjective quality evaluation of the signal to be measured. The popular subjective quality assessment methods are: (1) Double Stimulus Continuous Quality Scale (DSCQS, Double Stimulus Continuous Quality Scale); (2) Double Stimulus Damage Scale (DSIS, Double Stimulus Impairment Scale); (3) Single Stimulus Continuous Quality Scale (SSCQE, Single Stimulus Continuous Quality Scale) [Kramm (2007)].

The objective quality evaluation methods are mainly divided into three categories: Full-Reference (FR), Partially-Reduced-Reference (RR), and No-Reference (NR). The full reference quality evaluation mainly includes traditional evaluation methods based on full pixel distortion statistics and evaluation methods based on human visual system (HVS). The more popular partial reference evaluation methods are: based on feature extraction methods, based on harmonics. The method of intensity, based on the wavelet domain statistical model method and the SSIM method; no reference quality evaluation method (No-Reference, NR). Can be divided into: machine learning based algorithms and algorithms for distortion types. The machine learning-based algorithm obtains the image quality score by extracting the feature vector with strong image classification ability and combining with human subjective score (MOS) for nonlinear regression analysis.

2 Three method image quality evaluation

There are many commonly used image quality evaluation methods, which can be divided into subjective evaluation method and objective evaluation method. This paper is discussed and compared general objective quality evaluation method, such as peak signal to noise ratio method, structure similarity [Kumar, Singh, Mohan et al. (2011)], and Entropy of Primitive.

2.1 Peak signal to noise ratio

The basic principle of image objective quality evaluation is to compare the original image and the distorted image pixel by pixel to obtain the pixel-level error value, and finally the obtained statistical information is used as the evaluation standard. The objective quality evaluation methods of images mainly include: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Mean Absolute Error (MAE).

(1) Peak Signal-to-Noise Ratio (PSNR) is a method of expressing the ratio of the maximum possible power of a signal to the destructive noise power that affects its representation accuracy [Lee and Lim (2016)]. As shown in formula (1).

$$PSNR = 10 \log_{10} \frac{L^2}{MSE}$$
(1)

N represents the total number of pixels, L represents the dynamic range of the pixel, xi represents the pixel value of the original image, and yi represents the pixel value of the distorted image. Mean Square Error (MSE). As shown in formula (2).

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (x_i - y_i)^2$$
(2)

2.2 Objective quality evaluation method based on structural similarity

In order to be able to obtain an evaluation method consistent with the subjective feelings of the human eye, it is not possible to rely solely on the statistical method of full pixels, so that it is necessary to use the "human eye" and some characteristics of psychology to consider the process of human visual analysis in evaluation techniques. in. The structural similarity measure has a strong similarity to the perception of images [Méndezaguilar, Kellypérez, Berrielvaldos et al. (2017)], similar to the high-use function of the "human eye". The mathematical function model of SSIM is shown in Eq. (3).

$$SSIM(X,Y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$
(3)

X and Y represent input signals, μ_x represents the average luminance of the image signal, x_i represents the pixel value of the *i*-th pixel in the image, C_1 and C_2 are constant, and standard deviations σ_x and σ_y represent signal contrast.

2.3 Primitive entropy evaluation method

The primitive entropy is the statistic in the sparse representation, which represents the probability of use of each primitive. The combination of the statistical properties of the dictionary primitives in the sparse representation and the concept of Shannon's information entropy yields the Entropy of Primitive [Ramos and Mercère (2016)]. Shannon Entropy indicates the size of the maximum amount of information, which is a concise expression of the amount of information. The expression of Shannon's information entropy is shown in Eq. (4):

$$H(x) = -\sum_{x} P(x) \log_{2} [P(x)]$$
(4)

x represents a random variable, and P(x) represents an output probability function. For any input image Y, it is divided into several blocks y_1, y_2, \dots, y_N of the same size (the size in

this experiment is 8×8). These small blocks are now used as input signals for the K-singular value decomposition (K-SVD algorithm), and the complete dictionary D is trained. The sparse representation vector $\{x_i\}$ is obtained by the Orthogonal Matching Pursuit (OMP) algorithm, where xi corresponds to the block y_i .

After the sparse representation vector $\{x_i\}$ is obtained, the primitive corresponding to the value that is not zero in x is considered to be used once. As shown in Eq. (5)

$$t_i = \sum_{j=1}^N n_{j,i} \tag{5}$$

where N is the number of image blocks, t_i is the number of times each primitive is used, and n_{j_i} represents whether the *j*th image block uses the *i*th primitive. The calculation method of n_i is as shown in Eq. (6):

$$n_{j,i} = \begin{cases} 1, if \ x_{j,i} \neq 0\\ 0, otherwise \end{cases}$$
(6)

In the above formula, x_j represents the th coefficient of the sparse representation vector of the *j*th block image. This makes it possible to count the number of times each primitive in the dictionary is used, t_1, t_2, \dots, t_k . Then you can count the probability that each primitive is used, as shown in Eq. (7):

$$p_i = \frac{t_i}{\sum_{j=1}^k t_j} \tag{7}$$

Finally, similar to the entropy calculation method, the element entropy (EoP) is defined as the formula (8):

$$EoP = -\sum_{i=1}^{k} p_i \cdot \log p_i \quad (p_i \neq 0)$$
(8)

Figs. 1-3 show the reconstructed images of the three images of Lena, Einstein, and Plane in the test library at the primitive number $L=1\sim14$, and the PSNR and SSIM calculated from the original image. The trend of the elemental entropy (EoP) curve.



Picture of the test (a) Lena, (b) Einstein and (c) Plane



Figure 1: Lena image PSNR, SSIM, L with the EoP change curve

As can be seen from Fig. 1, when the EoP and SSIM curves are smooth (about L=7), the subjective quality of the image tends to be stable, and the human eye barely notices any change.



Figure 2: Plane image PSNR, SSIM, L with the EoP change curve



Figure 3: Einstein image PSNR, SSIM, L with the EoP change curve

As can be seen from the above three figures, as the number of primitives L increases, the reconstructed image quality (PSNR, SSIM) continues to increase [Rehna and Kumar (2014)]. Entropy of Primitive (EoP) also increases. When L reaches a certain value (about 7), the SSIM curve tends to be stable, and the EoP curve tends to be stable.

In order to use mathematical methods to prove subjective feelings, the Pearson correlation coefficient (PLCC) of 30 test images was calculated to measure the correlation between EoP and PSNR and SSIM.

First, a nonlinear model, such as Eq. (9), is used to fit PSNR-EoP and SSIM-EoP. After obtaining the model parameters, the predicted values of EoP are calculated by substituting into Eq. (9).

$$y = a_1 \left[\frac{1}{2} - \frac{1}{1 + e^{a_2(x - a_3)}} \right] + a_4 x + a_5$$
(9)

Then, the PLCC between the EoP predicted value and the EoP measured value is calculated by the formula (10), and the experimental result is shown in Fig. 4.



Figure 4: 30 test images of PSNR-EoP and PLCC SSIM-EoP

As can be seen from Fig. 4, EoP has a strong correlation with SSIM. In most cases, the PLCC of SSIM-EoP is larger than the PLCC of PSNR-EOP and the PLCC of SSIM-EoP is close to 1 [Shi, Jiang and Zhao (2016)], which means that EoP and SSIM show linear correlation, indicating that EoP can evaluate the subjective quality of the image.

In order to further explain why the value of EoP tends to be stable with the increase of the number of primitives L, this paper verifies. The histograms of the Lena, Einstein, and Plane images under different L primitives are counted, as shown in Figs. 5-7.



Figure 5: Histogram of Lena image under different L



Figure 7: Histogram of basic elements in different L images of Plane images

The histograms from above are summarized as follows:

(1) With the increase of L, the total number of times the primitives are used is increasing, and its distribution is gradually becoming stable, showing a strong regularity;

(2) When L=1, each image block can only be represented by one primitive, so that some primitives are used in a large amount;

(3) A large number of similar image blocks are repeated, and the most likely to be used is the same primitive.

(4) The reason why a large number of primitives are not used may be due to local similarity of the image, such as the background area of the image;

(5) With the increase of L, the distribution of primitives is gradually uniformized. The performance on the elemental entropy (EoP) is that as L increases from 1, the EoP

increases significantly. However, when L is increased to a certain value, although the number of primitives used, that is, the magnitude of the histogram is still increasing, the law of probability distribution is gradually stabilized, and the rate of change of EoP value gradually slows down and eventually stabilizes. It is verified that the value of EoP tends to be stable as the number of primitives L increases.

3 Primitive entropy model

The element entropy (EoP) is treated equally for all image blocks, and all image blocks contribute the same to the number of primitive uses. However, the degree of attention of the "human eye" is different in each image, which will bring higher demands to the processing of video images. Based on such considerations, the human eye attention model of the image and the element entropy are combined, and the results obtained by the human eye attention model are used to weight the number of primitives used, so that different regions of the image can be well distinguished. The method used in this section of the experiment is based on the human eye attention model represented by sparse features, as shown in Eq. (11):

$$t_i = \sum_{j=1}^N w_j \times n_{j,i} \tag{11}$$

The experimental results yielded similar results to EoP, as shown in Fig. 8, which are the EoP (AEoP) versus L curves for the Lena, Einstein, and Plane images based on the human eye attention model.



Figure 8: Lena, Einstein and Plane images of the AEoP change curve

AEoP was found to have similar statistical properties and was strongly correlated with SSIM and subjective quality.

3.1 Visual information system

It can be seen from the above experiments that there is strong robustness between elemental entropy (EoP) and image quality evaluation. It takes advantage of this property of primitive entropy to propose visual information (Visual Information, VI). Vision is a kind of human cognitive means and an important way for human beings to understand the objective world.

Fig. 9 shows the experimental results of a set of Lena images using four EoP curve results for JPEG-compressed images using different quantization factors (QF) [Vaksman, Zibulevsky and Elad (2016)]. It can be seen that the EoP curve of the distorted image also

maintains a similar trend and tends to be stable as the L increases. However, the EoP peaks under these different quantization factors (QF) are different. As the quantization factor increases, the visual effect of the image is closer to the original image, and the peak of EoP gradually increases, and gradually approaches the EoP peak of the original image.



Figure 9: EoP curves of Lena images under different QF

Let X denote the input image, and EoP_i denote the value of EoP when L=*i*,

where $1 \le i \le N$, and N in the experiment takes the empirical value 14. Eq. (12) defines the threshold \tilde{l} , which is the L value when the EoP value tends to be stable:

$$\tilde{l} = \arg\min_{i}, \qquad s.t. \frac{EoP_i - EoP_{i-1}}{\max_{i}(EoP_j) - \min_{i}(EoP_j)} < \varepsilon$$
(12)

In the formula, ε is a constant, which is 0.01 in this experiment. It is shown that after L exceeds this threshold \tilde{I} , the EoP curve will tend to be smooth. The EoP value of the threshold \tilde{I} point is the visual information of the image [Zhang Wang, Ma et al. (2014)], and the visual information (Visual Information, VI) is defined as shown in the formula (13).

$$VI = EoP_{\tilde{i}} \tag{13}$$

Next, statistics were performed on the experiment. The visual information (VI) of the JPEG compressed image obtained by the image under different quantization factors is counted, and the results of four images are shown in Fig. 10.



Figure 10: Relationship between VI and quantization factor of different images

It can be seen from the above figure that as the quantization factor (QF) increases, the image quality will also increase, and the estimation of image visual information (VI) tends to be stable, gradually approaching the amount of visual information of the original image.

3.2 JND model based on primitive entropy

The just-identifiable distortion (JND) is a threshold that indicates the tolerance of the human eye. If the nonlinear effect relationship of the human eye to different things is neglected, a non-linear relationship is used to express the superposition effect of brightness and texture. The just-identified distortion (JND) expression is shown in Eq. (14).

$$JND^{s}(x, y) = T^{t}(x, y) + T^{t}(x, y) - C^{tt} \times \min\{T^{t}(x, y), T^{t}(x, y)\}$$
(14)

(x, y) represents the brightness mask effect, $T^t(x, y)$ represents the texture mask effect, and C^{lt} represents the degree of superposition between the two factors. The size of the C^{lt} value determines the effect of the superposition effect. When the C^{lt} value is large, the superposition effect between the brightness mask and the texture mask is strong; when $C^{lt=1}$, the superimposed effect reaches the maximum value; when $C^{lt=0}$, the case where the superposition effect is minimum is zero. In many cases, the superposition effect is between the maximum and the minimum, i.e., $0 < C^{lt} < 1$.

PLP (perceptual lossless profile) refers to an image that is lossless in visual information generated by maximizing distortion. The reconstructed image \tilde{X} of the primitive using the threshold \tilde{l} is defined as a PLP. Experiments in the previous section have shown that the threshold \tilde{l} means that the visual information will no longer change significantly, then the image reconstructed at this threshold point is considered visually undistorted from the original image. With PLP, the maximum tolerable loss of visual information can be effectively estimated, and the smallest error that can be recognized by HVS can be effectively estimated, which is similar to the concept of JND. The new EoP-based JND model is then established, as shown in Eq. (15).

$$EJND[i, j] = abs\left(\tilde{X}[i, j] - X[i, j]\right)$$
(15)

In the formula, abs means taking the absolute value. EJND is the residual image of the PLP and the original image.



Figure 11: EJND images under different L

Fig. 11 shows the EJND image under different L. It can be seen that the energy of EJND does not change significantly after L is greater than 7, which is in line with the definition of PLP. Both the JND in the airspace and the JND in the frequency domain take advantage of the HVS feature and treat HVS as an unknown black box, a "bottom-up" modeling approach.

4 Visual information difference metrics

Since there is a strong correlation between the elementary entropy and the subjective feeling, the elementary entropy can be used to measure the visual information that an image brings to the human eye. Based on these properties of primitive entropy, this paper proposes a model of the Difference of Visual Information Metric (DVIM) as follows:

(1) respectively calculating the visual information value (VI) of the original image and the distorted image;

(2) using the visual information values of the original image and the distorted image to make a difference;

(3) the difference obtained is used as a measure of the difference.

This indicator is the difference in visual information, which can measure the size of the image visual information data. As the degree of image distortion continues to increase, the difference in visual information values (VI) between the original and distorted images is also increasing. Conversely, as the distorted image is closer to the original image, the difference in visual information values between the two decreases. The model of visual information difference metric (DVIM) is shown in Eq. (16).

$$DVI = \left| VI_{ref} - VI_{dis} \right| \tag{16}$$

 VI_{ref} and VI_{dis} are used to represent the visual information of the original image and the distorted image, respectively, and DVI is the difference between the visual information of the two.

Visual Information Difference Metric (DVIM) is a semi-reference quality evaluation method that does not require all the information of the original image. It only needs the visual information value VI_{ref} calculated by the original image, and the difference between the original image and the distorted image visual information. The value can evaluate the quality of the image, which facilitates the calculation process and improves the efficiency of video processing. At the same time, the visual information difference between the two distorted images can also be used as an indicator to evaluate the image quality.

5 Comparison experimental design and results

In order to verify the feasibility of visual information difference metrics evaluation (DVIM) in image quality evaluation, this paper applies this method to LIVE image database for a large number of experiments. At the same time, the SSIM method and the Wavelet marginal method were used to compare and test in the same image library. The experiment is as follows:

Experiment on the LIVE database, assuming that the size of the database is N, that is, contains N images. The results were calculated using five methods for calculating correlation, and the results were obtained as shown in Tab. 1.

Table	1:	Performance	comparison	of	different	quality	evaluation	methods	on	LIVE
databas	se									

IQA measure	Туре	PLCC	MAE	RMS	SRCC	KRCC
SSIM	FR	0.9642	6.1504	8.2267	0.9829	0.8640
Wavelet marginal	RR	0.8342	12.8152	17.2559	0.8617	0.6690
DVIM	RR	0.8803	11.5771	14.8530	0.9077	0.7340

As can be seen from the final data in the above table, the evaluation performances of visual information difference (DVIM) and Wavelet marginal are almost the same, and even have a large improvement. That is, the DVIM method can perform the same evaluation function as the currently popular image quality evaluation method.

(B) In order to further verify the effectiveness of the method, the scatter plots of SSIM, Wavelet and DVIM are plotted, as shown in Fig. 12.



Figure 12: Scatter point distribution of three kinds of objective quality assessment methods

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Fig. 12 shows a scatter plot of SSIM, Wavlet, and DVIM with subjective scoring, respectively. As can be seen from the figure:

(1) The result of Wavlet fitting is most linear, as shown in Fig. 12(b), but its distribution is too scattered and does not fit the subjective prediction well.

(2) The DVIM method is more concentrated, especially in the densely distributed and small values, which shows a good linear relationship with the subjective scores. This shows that the predicted results are similar to the subjective evaluation results, as shown as Fig. 12(c). Therefore, the method can predict the quality level of the image well, so the DVIM method can effectively evaluate the quality of an image.

(C) The DVIM method and the PSNR and SSIM methods are applied to the test standard images Lena, Einstain, and Plane. The results are shown in Figs. 13-15 The first image of the three sets of images is the original image, and the (b)-(d) images are images after geometric transformation such as translation, rotation, and scaling. (e) The images are all JPEG-compressed. As a result, the JPEG compression random selection quantization factor is 14.



Figure 13: Lena image under different transform evaluation index contrast. (a) Lena original image; (b) Right translation; (c) Counter Clockwise Rotation respectively (d); Amplification (e) After JPEG compression



Figure 14: Einstein image under different transform evaluation index contrast. (a) Original image; (b) Right translation; (c) Counter clockwise Rotation; (d) Zoom 1.1 times; (e) JPEG compression



Figure 15: Plane image under different transform evaluation index contrast. (a) Original image; (b) Right translation; (c) Counter Clockwise Rotation; (d) Zoom 1.1 times; (e) JPEG compression

From the final results, the PSNR method and the SSIM method are not as adaptable to the transformation of translation, rotation and scaling as DVIM, and the evaluation results given by these two transformations are very low, but the evaluation of the last JPEG compression is better than others. The changes of translation, rotation and zoom are much higher, which is obviously inconsistent with the subjective quality evaluation of "human eyes".

(D) The result calculated by the DVIM method indicates the difference in the amount of information contained in the two images, which is independent of the position of the pixel image, so that the distribution of the corresponding pixel points caused by the geometric transformation can be effectively avoided. The subjective feeling of "human eyes".

Therefore, the visual information difference measure (DVIM) can meet the subjective judgment of the "human eye" to a certain extent.

6 Conclusion

This paper discusses an image quality assessment method that replaces the subjective perception of the human eye, the visual information difference metric (DVIM). After several sets of test experiments, the method and the current popular quality evaluation have greatly improved the geometrical changes of the image, and the method is independent of the position of the pixel image, effectively avoiding the correspondence caused by the geometric transformation. The problem of scattered pixel distribution is more in line with the subjective feeling of "human eye", which proves that this method is an effective image quality evaluation method.

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References

Bi, S. (2017): Improved method for predicting the peak signal-to-noise ratio quality of decoded images in fractal image coding. *Journal of Electronic Imaging*, vol. 26, no. 1, pp. 13-24.

Digne, J.; Galin, E.; Peytavie, A. (2016): Sparse representation of terrains for procedural modeling. *Computer Graphics Forum*, vol. 35, no. 2, pp. 177-187.

Hu, W. K.; Wu, C. H.; Lin, C. H. (2014): Economic approximate-k color printing algorithm. *Multimedia Tools & Applications*, vol. 72, no. 1, pp. 151-166.

Jiang, G.; Peng, Z. (2016): Video quality assessment method motivated by human visual perception. *Journal of Electronic Imaging*, vol. 25, no. 6, pp. 61-63.

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Kramm, M. (2007): Compression of image clusters using Karhunen Loeve transformations. *Human Vision and Electronic Imaging XII. International Society for Optics and Photonics*, pp. 101-106.

Kumar, B.; Singh, S. P.; Mohan, A.; Anand, A. (2011): Novel MOS prediction models for compressed medical image quality. *Journal of Medical Engineering & Technology*, vol. 35, no. 3-4, pp. 161-171.

Lee, D.; Lim, S. (2016): Improved structural similarity metric for the visible quality measurement of images. *Journal of Electronic Imaging*, vol. 25, no. 6, pp. 15-63.

Méndezaguilar, E. M.; Kellypérez, I.; Berrielvaldos, L. R.; Delgadoatencio, J. A. (2017): Simulation and analysis of light scattering by multilamellar bodies present in the human eye. *Biomedical Optics Express*, vol. 8, no. 6, pp. 29-30.

Ramos, J. A.; Mercère, G. (2016): Image modeling based on a 2-D stochastic subspace system identification algorithm. *Multidimensional Systems & Signal Processing*, vol. 28, no. 4, pp. 1-33.

Rehna, V. J.; Kumar, M. K. J. (2014): An improved algorithm for image compression using geometric image approximation. *International Journal of Electrical Electronics & Data Communication*, vol. 2, no. 6.

Shi, W.; Jiang, F.; Zhao, D. (2016): Image entropy of primitive and visual quality assessment. *IEEE International Conference on Image Processing*, pp. 87-91.

Vaksman, G.; Zibulevsky, M.; Elad, M. (2016): Patch-ordering as a regularization for inverse problems in image processing. *Siam Journal on Imaging Sciences*, vol. 9, no. 1, pp. 287-319.

Zhang, X.; Wang, S.; Ma, S.; Liu, S.; Gao, W. (2014): Entropy of primitive: a top-down methodology for evaluating the perceptual visual information. *Visual Communications and Image Processing*, pp. 1-6.