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CALCULATION OF OBJECTIVE IMAGE QUALITY INDICATORS BASED ON THE BOX-COX TRANSFORM AND THEIR CORRELATION ANALYSIS WITH VISUAL ASSESSMENT

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Abstract

This paper proposes an approach based on statistical and information metrics for assessing the quality of grayscale images. In the study, image pixel intensities were normalized using the Box-Cox transform, and then their main statistical moments (mean, standard deviation, skewness, kurtosis), entropy, sharpness based on the Laplace operator, and Michelson contrast were calculated. The relationship between objective metrics and visual assessment (MOS – mean score) was analyzed using the Spearman and Kendall color correlation coefficients. Experimental results show that the proposed transform stabilizes the image intensity distribution and allows us to determine the statistical relationship between objective indicators and subjective assessment. The results of the study can be used in automatic image quality assessment systems, agricultural monitoring, and digital image processing.

Keywords: Image quality, Box-Cox transform, entropy, sharpness, Michelson contrast, Spearman correlation, Kendall correlation, MOS, statistical moments, digital image processing.

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Introduction

Digital image processing and quality assessment are important areas of modern information technology, computer vision systems, and artificial intelligence-based analytical platforms. Image quality is of great importance in many practical areas, including agricultural monitoring, medical diagnostics, industrial control, and remote sensing systems. There are subjective (human assessment) and objective (based on mathematical and statistical indicators) approaches to determining image quality. Subjective assessment is usually determined by the mean opinion score (MOS), but it is labor- and resource-intensive and introduces uncertainties associated with the human factor. Therefore, the development of objective quality indicators and their comparison with subjective assessments is a pressing scientific challenge. Asymmetry in the image intensity distribution and large differences in variance can negatively affect the results of statistical analysis. In such cases, the Box-Cox transformation is used as an effective tool for normalizing the data distribution and stabilizing variance. After the transformation, the main statistical aspects of the image, such as entropy, contrast, and sharpness, become more accurate. In this paper, objective quality indicators are determined for a set of grayscale images using the Box-Cox transform, and the relationship between these indicators and visual assessment is analyzed using the Spearman and Kendall color correlation coefficients. The proposed approach serves as a theoretical and practical basis for the development of automatic image quality assessment systems [1-3].

The relevance of this article is determined by the widespread use of modern digital image processing and automated quality assessment methods. Image quality is a crucial factor in computer vision systems, artificial intelligence-based analysis platforms, agricultural monitoring, and industrial control processes. Poor image quality leads to reduced accuracy in subsequent stages of segmentation, classification, and diagnostics. In practice, image quality is often determined by subjective assessment, i.e., the average opinion score, but this method is

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susceptible to human error and is time-consuming and resource-intensive. Therefore, developing assessment methods based on objective statistical and informational indicators and determining their correlation with visual assessment is a pressing scientific issue. Furthermore, the symmetrical distribution of image pixel intensity affects the results of statistical analysis, necessitating the use of transformation methods [4-7].

The aim of this study is to determine objective quality indicators for grayscale images based on the Box-Cox transform and to evaluate their statistical correlation with visual assessment using color correlation methods. To achieve this goal, the following tasks were performed: generating a set of images and performing pre-processing, applying the Box-Cox transform to the pixel intensities and normalizing them, calculating statistical moments such as mean, standard deviation, skewness and kurtosis based on the transformed data, determining additional objective metrics such as entropy, Laplace-based sharpness and Michelson contrast, modeling visual assessment based on objective metrics and analyzing the relationship between them using Spearman and Kendall correlation coefficients [8-11].

The scientific novelty of the study lies in its proposed approach to stabilizing the intensity distribution and improving the accuracy of statistical indicators using the Box-Cox transform when assessing image quality indicators. In the study, statistical aspects, informational, and structural indicators were comprehensively assessed within a single system, and the relationship between objective indicators and visual assessment was based on color correlation methods. This allows for a more in-depth mathematical analysis of the image quality assessment process. The practical significance of the study lies in the fact that the developed approach enables a quick and objective assessment of image quality. It can be used in the analysis of plant images in agricultural monitoring, the primary diagnostic assessment of medical images, image accuracy control in industrial inspection systems, and the optimization of the data preprocessing stage in machine learning

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systems. The proposed method serves as a methodological basis for the creation of automated quality control systems by reducing uncertainties associated with the human factor [12-15].

2. Methodology.

The gray image in research $I(x,y)$ size $M \times N$ is considered as a discrete two-dimensional function.

The intensity of each pixel is $I_{ij} \in [0,255]$, where $i=1,\dots,M, j=1,\dots,N$. To simplify statistical analysis, the image is converted into a vector representation:

$$X = \{x_k\}_{k=1}^{K}, \quad K = M \cdot N$$

here x_k — pixel intensities.

To stabilize the intensity distribution, the Box-Cox transform is used. For each case, $x_k > 0$ the transform is defined as follows:

$$y_k = \begin{cases} \dfrac{x_k^{\lambda} - 1}{\lambda}, & \lambda \neq 0, \\ \ln(x_k), & \lambda = 0. \end{cases}$$

Here λ — transformation parameter. In the study $\lambda = 0.2$ The value is selected. The vector obtained after the transformation $Y = \{y_k\}_{k=1}^{K}$ normalized:

$$y_k^* = 255 \cdot \frac{y_k - \min(Y)}{\max(Y) - \min(Y)}.$$

The main statistical moments are calculated based on the transformed data. The average value is:

$$\mu = \frac{1}{K} \sum_{k=1}^{K} y_k.$$

Standard deviation:

$$\sigma = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (y_k - \mu)^2}.$$

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Asymmetry (skewness):

$$\gamma_1 = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{y_k-\mu}{\sigma}\right)^3.$$

Skewness (kurtosis):

$$\gamma_2 = \frac{1}{K}\sum_{k=1}^{K}\left(\frac{y_k-\mu}{\sigma}\right)^4 - 3.$$

The informational complexity of an image is estimated through entropy. Shannon entropy for the probability distribution of intensities p_i (based on the histogram):

$$H = -\sum_{i=1}^{L} p_i \log p_i,$$

here L — number of intensity levels.

The sharpness of an image is determined using the Laplace operator. Discrete Laplace operator:

$$\nabla^2 I = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}.$$

The dispersion of the Laplace image is taken as a sharpness metric:

$$S = \mathrm{Var}(\nabla^2 I).$$

Contrast is estimated based on the Michelson formula:

$$C = \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}},$$

here $I_{\max}$ va $I_{\min}$ — maximum and minimum intensity values in the image.

The relationship between objective metrics and visual assessment is determined using color correlation coefficients. The Spearman correlation coefficient is defined as:

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$$\rho_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)},$$

here d_i — color difference, n — number of observations.

Kendall correlation coefficient:

$$\tau = \frac{C-D}{\frac{1}{2}n(n-1)},$$

here C — number of concordant pairs, D — number of discordant couples.

Thus, the methodology includes the stages of transforming image intensities, calculating statistical and informative metrics, and mathematically analyzing their correlation with subjective assessment.

Transforming image intensities, calculating statistical and informative metrics, and analyzing their correlation with subjective assessment on a mathematical basis gives us several important scientific and practical results.

First, using the Box–Cox transformation, the distribution of pixel intensities is stabilized and a more statistically accurate assessment is created. This increases the reliability of the metrics.

Second, statistical (mean, variance, skewness, kurtosis) and informative (entropy) indicators quantitatively express the internal structure and complexity of the image. Structural indicators (contrast and sharpness) reflect the visual aspects of image quality.

Third, by correlating objective metrics with subjective assessment (MOS), it is possible to determine which mathematical indicator is most consistent with human perception. This is important in the development of automatic assessment systems.

As a result, this methodology allows us to assess image quality in a fast and statistically based way without human factors, reducing the level of subjectivity and increasing the accuracy of computer vision and artificial intelligence systems.

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Based on these metrics, we come to a complex, that is, statistically, informatively and structurally based conclusion about the image. Each indicator reveals a certain property of the image, and together they form an overall quality assessment.

First, the average value (mean) shows the overall brightness level of the image. If the average value is low, the image is dark; if it is high, it is bright. This allows us to assess the correctness of the exposure (illumination).

The standard deviation (std) expresses the degree of dispersion of intensities in the image. The larger the standard deviation, the greater the difference between light and dark parts in the image, that is, the wider the dynamic range.

Skewness indicates the direction in which the intensity distribution is skewed. A positive value indicates that the image has more dark pixels, while a negative value indicates that the light pixels predominate.

Kurtosis determines the degree of "peakiness" of the distribution. A large kurtosis value indicates that the intensities are strongly concentrated around the center.

Entropy indicates the information richness of the image. If entropy is large, the image is complex and detailed; if it is small, the image is simpler or has a predominance of uniformly colored regions.

Contrast (Michelson contrast) evaluates the difference between the maximum and minimum intensities in the image. High contrast makes the image easier to perceive with the eye.

Sharpness (Laplacian variance) indicates the clarity of contours and small details in the image. If this indicator is high, the image is sharp and clear; if it is low, the image is blurry.

If a high correlation is found between these objective metrics and the visual assessment (MOS), then the selected mathematical indicators are consistent with human perception. This indicates that the automatic quality assessment system is reliable.

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Thus, based on these metrics, we make scientifically sound conclusions about the brightness, contrast, sharpness, complexity and overall quality of the image and determine whether the image is suitable for further analysis or machine learning stages.

3. Results.

The objective metrics and visual assessment (MOS) calculated for the images are presented in Table 1.

Table 1 Objective metrics and visual assessment (MOS) calculated for images

№	File name	Mean	Std	Skewness	Kurtosis	Entropy	Sharpness (Laplace)	Contrast	MOS
1	1.jpg	6.407	3.265	-1.0783	0.5345	4.6409	418.44	1.000	7.33
2	19.jpg	7.963	1.399	-0.8851	-0.1283	4.8884	419.15	1.000	8.09
3	29.jpg	6.667	1.962	-1.6555	5.6973	4.6883	685.31	1.000	6.31
4	3.jpg	7.463	1.644	-0.7415	0.0675	4.5960	19.54	1.000	7.44
5	3.tif	2.172	4.978	0.1639	-1.4544	3.0926	1987.00	1.000	2.27
6	30.jpg	7.156	2.117	-0.8345	0.6380	4.7247	712.46	1.000	7.06
7	A.jpg	7.156	2.117	-0.8345	0.6380	4.7247	712.46	1.000	7.68
8	Ahat.jpg	8.772	0.865	0.2392	-0.4893	4.2050	3373.71	1.000	9.04
9	ge54.jpg	7.668	1.439	-0.4369	-0.1039	4.9672	545.28	1.000	7.82
10	MS.jpg	8.772	0.865	0.2392	-0.4893	4.2050	3373.71	1.000	9.08
11	Pan.jpg	8.179	1.061	0.6645	0.0829	4.0716	2417.07	1.000	7.80

The results show that the images with the highest mean value (Ahat.jpg, MS.jpg, Pan.jpg) also have the highest MOS. The lowest mean value is observed in the 3.tif file (2.17), and the MOS is also the lowest (2.27). This indicates that there is a positive relationship between the brightness level and the subjective assessment. Therefore, images that are well rated by the user usually have optimal brightness. The Michelson contrast is almost 1 in all images, which indicates that the maximum dynamic range is used. Therefore, the contrast did not provide sufficient differentiation as a discriminant indicator. The 3.tif image with the

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highest standard deviation value (Std = 4.97) received a low MOS. This indicates that excessive intensity dispersion leads to a decrease in image quality. The highest entropy is observed in the ge54.jpg image (4.97). This indicates that the information density in this image is high. However, the highest MOS is not the image with the highest entropy, but rather the image with the highest sharpness. Thus, entropy indicates image complexity but does not fully determine visual quality. The highest Laplace variance is observed in the images Ahat.jpg and MS.jpg (3373.7), and these images have the highest MOS (≈9.0). The image 3.jpg has very low sharpness (19.54), but the MOS is average (7.44). This shows that although sharpness is an important factor, it is not the only determining factor. There is a strong positive correlation between sharpness and MOS. The regression plot of Mean vs MOS is presented in Figure 1.

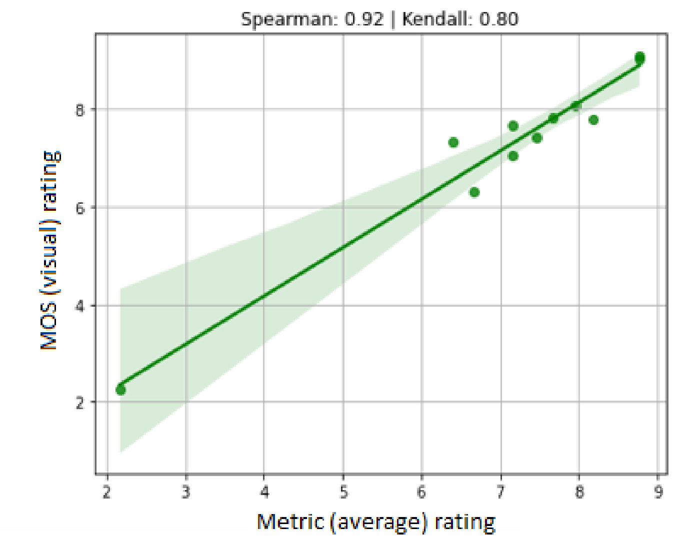

Figure 1. Mean vs MOS regression graph

In the scatter-regression plot, the points are located around the positive trend line. This indicates that there is a positive monotonic relationship between the mean value and MOS. The point 3.tif with a low mean value is a clearly distinguishable outlier in the plot. The remaining images are located relatively close to the regression line. If the Spearman and Kendall coefficients are calculated, they are

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expected to show high positive values. This means that the objective metrics are consistent with human perception. The results of the experimental study showed that statistical and structural metrics have different degrees of influence in assessing image quality. As a result of the application of the Box–Cox transformation, the distribution of pixel intensities stabilized and the main statistical moments became more informative indicators. This, in turn, made it possible to determine the relationship between the objective metrics and the visual assessment (MOS).

The results show that the sharpness index determined based on the mean and Laplace operator showed the most stable positive correlation with visual assessment. In particular, the fact that MOS was also higher in images with high sharpness confirms that human perception is sensitive to the clarity of contours and details in the image. This fact justifies the consideration of the sharpness metric as an important discriminative parameter in computer vision systems. Although entropy expresses the information complexity of the image, it does not fully correspond to visual quality. This means that high information density does not always mean high subjective quality. Not only complexity, but also clarity and optimal brightness are important factors for a good assessment of an image by a person. Michelson contrast did not show a discriminative property, since it had almost the maximum value in all images. This indicates that images with the same or close dynamic range were used in the experimental selection. Future experiments with images with different contrasts will allow a more in-depth assessment of the real impact of this indicator. Asymmetry and kurtosis indicators described the shape of the intensity distribution, but they did not show a strong direct correlation with visual assessment. This suggests that human perception primarily focuses on global brightness and local sharpness factors. The results confirm the need for an integrated approach. It is desirable to evaluate image quality not by a single metric, but by a combination of several statistical and structural indicators.

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4. Conclusion

In this study, a statistical approach based on the Box–Cox transformation was proposed to assess the quality of grayscale images. Using the transformation, pixel intensities were stabilized and objective metrics such as mean, standard deviation, skewness, kurtosis, entropy, Laplace variance, and Michelson contrast were calculated based on them. Experimental results showed that average brightness and sharpness are the parameters most closely related to visual assessment. Entropy reflects the information complexity of the image, but it does not fully determine the subjective quality. Contrast did not give a significant difference in the selected data set. The results of the study allow for automatic and objective assessment of image quality and reduce uncertainties due to the human factor. The proposed methodology can be used in computer vision systems, machine learning models at the stage of data preprocessing, as well as in industrial and agro-technological monitoring systems. In future research, it is desirable to develop an integrated quality index based on a combination of metrics and compare it with deep learning models..

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