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DETERMINATION OF THE PRIORITY OF RASTER IMAGE QUALITY FACTORS USING THE RANKING METHOD

Theoretical principles regarding the quality of raster images are provided. A wide range of application areas of raster graphic information is defined, including education, medicine, and printing. An analysis of recent studies and publications is conducted. The aim and main objectives of the research are formulated. A methodological approach to identifying the priority levels of factors influencing raster image quality based on ranking is demonstrated. A set of influencing factors is distinguished, including resolution, color depth, color model, file format, file size, image dimensions, compression level, brightness, saturation, and sharpness. To structure the interrelationships among these parameters, predicate logic constructions are applied. It is established that certain factors may exert both direct and indirect influence on other elements. Tables are developed to represent the connections for each factor. Hierarchical trees of direct and indirect influences and dependencies are constructed. An example of hierarchical trees for one of the selected factors is presented. Based on the analysis of the structure of interconnections, the ranking of quality factors is carried out. For this purpose, the number of each type of connection is counted, and corresponding weight coefficients are introduced. Positive weight values are assigned to influences, while negative ones are assigned to dependencies. The importance scores of the factors are calculated. A normalization of the values is performed to transform the scale into a positive domain. A final evaluation is conducted, taking into account the normalization coefficient. Factor ranks and the corresponding levels of priority are determined. Input data and ranking results are presented in tabular form. A model that reflects the priority levels of influencing factors on raster image quality is developed. The obtained results can be applied for image quality assessment based on fuzzy logic and machine learning methods, followed by the development of a corresponding fuzzy system.

Keywords: ranking, factor, priority, raster image, quality assessment, priority influence model, interrelation between factors, direct influence, indirect influence.

Introduction. A raster image is defined as a digital representation of visual information in the form of a regular matrix of pixels. Each pixel is assigned numerical values of color and brightness. However, the quality of the image is influenced by technical parameters such as color model, resolution, color depth, and others. It is noted that all parameters have different degrees of influence on quality [1].

The application of raster images covers numerous domains, including education, medicine, and printing. In educational e-textbooks and instructional visualizations, clarity and color accuracy are considered essential for conveying information. In medicine, raster formats are used to ensure precise rendering of CT, ultrasound, and X-ray results, where each pixel may contain critically important diagnostic data. In the printing industry, image quality determines the clarity and color accuracy of advertising, newspaper, magazine, or book products [2].

In this context, the need for formalizing the priority of quality-influencing factors is recognized. One of the modern and reliable methods for determining their significance is represented by ranking.

Literature review. Recent scientific studies indicate the active development of methods for image assessment, restoration, and optimization. Significant attention is paid to identifying and describing the key parameters of image quality.

In [3], a model for image restoration based on the Swin Transformer is proposed. This study addresses image quality issues related to resolution, noise, and artifacts. In [4], an image reconstruction algorithm for medical purposes is developed, which combines noise reduction and resolution enhancement functions based on a neural network model. According to clinical test results, the model provides significantly higher diagnostic performance compared to classical reconstruction methods. Study [5] focuses on scanned documents at three resolution levels – 75, 150, and 300 dpi. The results show that structural detail in images is significantly improved at 300 dpi. Thus, studies [3–5] confirm the importance of high resolution for accurate reproduction of fine details.

A separate category of research is devoted to the specifics of image rendering in virtual and augmented reality. In particular, [6] introduces a model for evaluating image quality in the high-dynamic environment of AR/VR displays. The authors note that classical metrics fail to consider the distortions characteristic of this type of visualization, such as geometric deformation effects and focal depth changes.

In [7], image quality is studied through psychophysical tests. Subjective perception of quality varies depending on contrast, colorfulness, and sharpness. The authors systematically modify these parameters and obtain data that allow the construction of an image quality model. The findings in [8] demonstrate that the use of lossy compression algorithms (JPEG, JPEG 2000, JPEG XL) leads to the appearance of artifacts that negatively affect quality. In [9], a method is presented that analyzes gradient and texture distortions. The results indicate that traditional IQA metrics often fail to detect subtle compression defects. This study emphasizes the need to consider compression as a key quality factor.

Several studies also focus on file format comparison [10, 11]. For example, comparisons of AVIF, JPEG XL, and WebP reveal that AVIF achieves minimal file size without loss of sharpness, color depth, or saturation. JPEG XL offers flexible options for preserving original images and supports a wide color gamut (XYB), while AVIF preserves gradients better. Study [12] highlights the importance of converting from RGB to CIELab to enhance the perception of brightness and saturation in specific environments. This underlines the importance of file format and color model for overall quality.

Study [13] also emphasizes that various factors, including contrast, saturation, and sharpness, exert different effects on perception by both human users and machines.

An important research direction is associated with the development of combined quality metrics. Study [14] proposes a new generalized metric that integrates FSIM, SSIM, and VIF. Validation is conducted on the TID2013 and PIPAL datasets. These findings support the relevance of constructing composite quality assessments as alternatives to individual criteria.

All mentioned works confirm that raster image quality is determined by a set of interrelated factors. However, insufficient attention is paid to the development of comprehensive models for parameter significance. This highlights the relevance of research aimed at ranking quality parameters and determining their priority.

The aim and objectives of the study. The aim of the study has been defined as the determination of ranks and priority levels of factors that influence the quality of raster images using the ranking method.

To achieve this aim, the following tasks have been set:

– hierarchical trees of interrelations among raster image quality factors have been developed;

– priority levels of raster image quality factors have been identified, and a model of priority influence of these factors has been constructed.

Development of hierarchical trees of interrelations between factors. In a previous study, a set of factors influencing raster image quality is distinguished [1]: $I = \{I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9, I_{10}\}$, where I_1 – resolution, I_2 – color depth, I_3 – color model, I_4 – file format, I_5 – file size, I_6 – image dimensions, I_7 – compression, I_8 – brightness, I_9 – saturation, I_{10} – sharpness. These factors represent the main parameters and characteristics of images. Undoubtedly, some factors are dependent on each other; that is, a factor I_i can influence factor I_j. It is evident that under such conditions, I_j depends on I_i. Factor I_i exerts an indirect influence on I_k if I_i directly influences I_j, and I_j in turn influences I_k. If I_i directly influences both I_j and I_k, and I_j also directly influences I_k, then I_i is considered to exert both direct and indirect influence on I_k. To formalize these statements, predicate logic constructions are used: $\xrightarrow{(1)}$ – direct influence (first-order influence); $\xrightarrow{(2)}$ – indirect influence (second-order influence); $\xleftarrow{(1)}$ – direct dependence (first-order dependence); $\xleftarrow{(2)}$ – indirect dependence (second-order dependence); $\wedge$ – logical conjunction (logical "and"); $\exists$ – existential quantifier ("there exists such $I_j \in I$, that..."); $\Leftrightarrow$ – logical equivalence [15]. Expressions reflecting the principles of forming connections between factors for $I_i, I_j, I_k \in I$ are formulated as follows:

$$\begin{gathered} I_i \xrightarrow{(1)} I_j;\ I_j \xleftarrow{(1)} I_i; \\ I_i \xrightarrow{(2)} I_k \Leftrightarrow \exists I_j \in I : I_i \xrightarrow{(1)} I_j \wedge I_j \xrightarrow{(1)} I_k; \\ I_k \xleftarrow{(2)} I_i \Leftrightarrow \exists I_j \in I : I_k \xleftarrow{(1)} I_j \wedge I_j \xleftarrow{(1)} I_i. \end{gathered} \quad (1)$$

The interrelations of raster image quality factors are presented in Table 1. Experts from the subject area are involved in determining the sets of dependent factors [16]. The absence of a connection is indicated by the symbol ∅.

Table 1 – Direct influences of factors

Analyzed Factor	Set of Dependent Factors
I_1	$\{I_5, I_6, I_{10}\}$
I_2	$\{I_5, I_8, I_9\}$
I_3	$\{I_2, I_4, I_9\}$
I_4	$\{I_5, I_7, I_8, I_{10}\}$
I_5	∅
I_6	$\{I_5\}$
I_7	$\{I_5, I_{10}\}$
I_8	∅
I_9	∅
I_{10}	∅

Taking into account second-order transitive relationships based on the data from Table 1, sets of indirect dependencies are formed (Table 2).

Table 2 – Indirect Influences of the Factors

Analyzed Factor	Set of Dependent Factors
I_1	$\{I_5\}$
I_2	∅
I_3	$\{I_5, I_7, I_8, I_9, I_{10}\}$
I_4	$\{I_5, I_{10}\}$
I_5	∅
I_6	∅
I_7	∅
I_8	∅
I_9	∅
I_{10}	∅

Based on the data from Table 1 and Table 2, hierarchical connection trees are developed, which visualize first- and second-level influences and dependencies.

These trees serve as a convenient tool for calculating the number of relationships.

The tree diagrams for the selected factor are presented in Fig. 1, as it is the most illustrative in terms of the number and diversity of established connections.

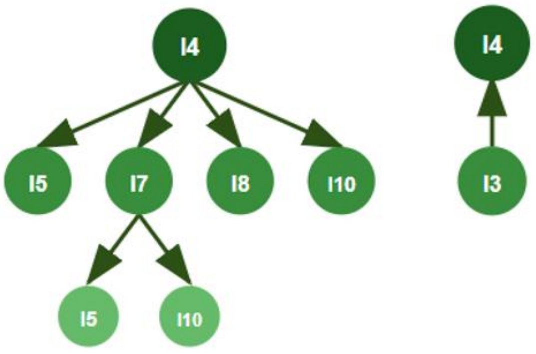

Fig. 1. Hierarchical trees of direct and indirect connections for factor I_4

Similar visualizations are constructed for the remaining factors. These hierarchical trees serve as the foundation for subsequent ranking.

Determination of Priority Levels of Factors. The determination of the ranks of factors affecting raster image quality is carried out based on the weight coefficients $W = \{w_1, w_2, ..., w_n\}$, where n is defined as the number of factors. A weight coefficient w_{ij} is interpreted as the share of a factor's influence on the overall result. At least one factor is identified for which the weight value w_{ij} is the maximum.

Initial ranks are assigned based on the number of incoming and outgoing arcs in the graph. The types of relationships (influence/dependence) and their order (direct or indirect) are also recorded. Each factor is characterized by a different level of influence; a situation of full equivalence (i. e. $w_{ij} = w_{ik}$) is considered impossible. This condition ensures the determinacy of the hierarchy and allows the avoidance of multiple interpretation scenarios.

To account for both direct and indirect influences and dependencies, an extended weighting system is introduced. Let x_{ij} denote the number of connections of a certain type for the j-th factor, where $i = 1$ corresponds to direct influences, $i = 2$ to indirect influences, $i = 3$ to direct dependencies, and $i = 4$ to indirect dependencies. In this context, the weights of influences always take positive values $(w_1 > 0, w_2 > 0, w_2 = w_1/2)$, while the weights of dependencies are assigned negative values $(w_3 < 0, w_4 = w_3/2)$. It is considered reasonable to define that $|w_1| = |w_2| \text{ and } |w_3| = |w_4|$, since influences and dependencies differ in direction but are assumed to possess equal importance in absolute terms. Based on the above theoretical assumptions, the following values are adopted: $w_1 = 10$, $w_2 = 5$, $w_3 = -10$, $w_4 = -5$. The final weight of a factor is calculated by taking into account all types of connections using the following formula:

$$I_{ij} = \sum_{i=1}^{4} \sum_{j=1}^{n} x_{ij} w_i . \qquad (2)$$

The main input data and the results of calculations according to the proposed methodology are presented in Table 3.

Since the weights w_1 and w_2 are positive, while w_3 and w_4 are negative, the following inequalities are logically observed: $I_{1j} > 0$, $I_{2j} > 0$, $I_{3j} < 0$ and $I_{4j} < 0$. To normalize and shift the scale into the positive domain, the following expression is used:

$$\triangle_j = \max|I_{3j}| + \max|I_{4j}|, (j = 1, 2, ..., n). \qquad (3)$$

The final normalized weight values are calculated as follows:

$$I_{Fj} = \sum_{i=1}^{4} \sum_{j=1}^{10} \left(x_{ij} w_i + \triangle_j \right). \qquad (4)$$

The highest total weight of a factor I_{Fj} corresponds to the highest rank value R_j. The priority level of a factor P_j is defined as the reciprocal of its rank R_j, meaning that the most influential factor is the one with the maximum rank [15].

Based on the factor priorities presented in Table 3, a hierarchical model of factor importance is constructed (Fig. 2).

Table 3 – Ranking of raster image quality factors

Factor j	x_{1j}	x_{2j}	x_{3j}	x_{4j}	I_{1j}	I_{2j}	I_{3j}	I_{4j}	I_{Fj}	Rank R_j	Priority P_j
1	3	1	0	0	30	5	0	0	105	8	3
2	3	0	1	0	30	0	-10	0	90	7	4
3	3	7	0	0	30	35	0	0	135	10	1
4	4	2	1	0	40	10	-10	0	110	9	2
5	0	0	5	4	0	0	-50	-20	0	1	10
6	1	0	1	0	10	0	-10	0	70	5	6
7	2	0	1	1	20	0	-10	-5	75	6	5
8	0	0	2	2	0	0	-20	-10	40	3	8
9	0	0	2	1	0	0	-20	-5	45	4	7
10	0	0	3	2	0	0	-30	-10	30	2	9

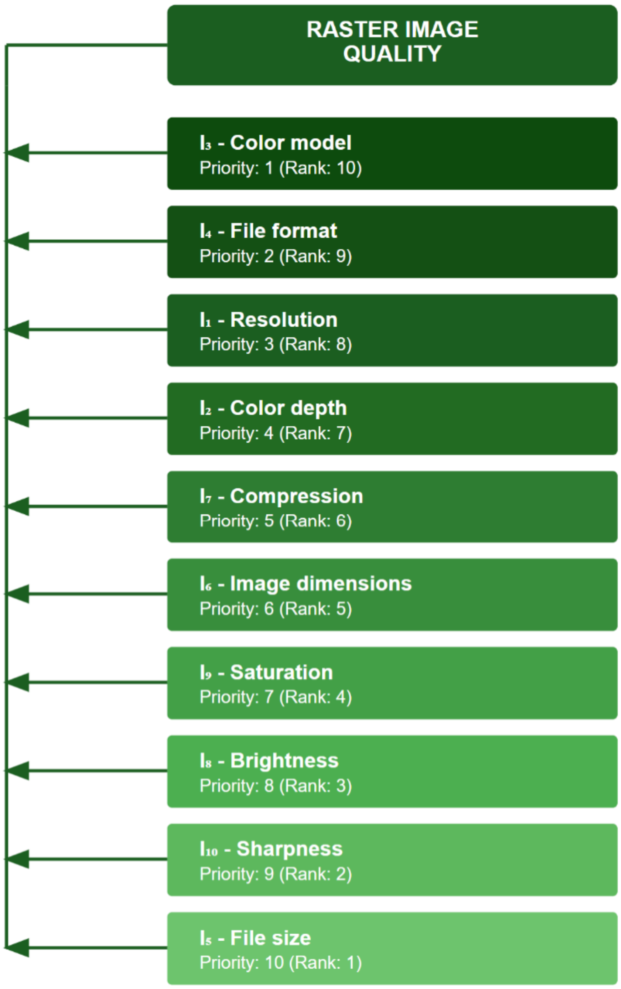

Fig. 2. Priority model of raster image quality factors

For the analyzed process, the most significant influence is exerted by factor I_3. The next in priority are considered to be I_4 (priority 2, rank 9) and I_1 (priority 3, rank 8). These factors are recognized as playing a crucial role in maintaining the technical parameters of the image and ensuring cross-platform compatibility. Medium-level importance is assigned to I_2, I_7 and I_6, which receive intermediate priority values (from 4 to 6), reflecting their relevance both to hardware rendering of color components and to the efficiency of graphic data storage and transmission. The lowest priorities are attributed to I_9, I_8, I_{10} and I_5 (ranks from 4 to 1). The reduced importance of these factors within the overall set is explained by their modifiability during post-processing without significant degradation of general image quality.

Conclusions. The ranking of ten key factors affecting raster image quality is carried out. In order to formalize the interrelation system among resolution, color depth, color model, file format and size, image dimensions, compression level, brightness, saturation, and sharpness, hierarchical trees of influences and dependencies are constructed. Based on the ranking results, it is found that the most influential factor on image quality is the color model $\left(R_j = 10,\, P_j = 1\right)$, while the least influential one is the file size $\left(R_j = 1,\, P_j = 10\right)$. A clear hierarchy of raster image quality factors is obtained and is presented through a priority-based factor model.

The main limitation of the study is associated with the potential subjectivity of experts when defining the set of major factors influencing raster image quality.

Future research directions include the incorporation of linguistic descriptions of relationship types by introducing additional coefficients, as well as the refinement of factor weights through multi-criteria optimization. The practical value of this work is seen in providing a theoretical foundation for the development of an interactive system for determining the significance of image quality factors.

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ВИЗНАЧЕННЯ ПРІОРИТЕТНОСТІ ФАКТОРІВ ЯКОСТІ РАСТРОВИХ ЗОБРАЖЕНЬ ЗА МЕТОДОМ РАНЖУВАННЯ

Наведено теоретичні положення щодо якості растрових зображень. Означено широкий перелік галузей використання растрової графічної інформації: в освіті, медицині, поліграфії тощо. Проведено аналіз останніх досліджень та публікацій. Сформовано мету та основні завдання дослідження. Продемонстровано методологічний підхід до визначення рівнів пріоритетності факторів впливу на якість растрових зображень на основі ранжування. Виокремлено множину факторів, серед яких: роздільна здатність, глибина кольору, колірна модель, формат файлу, розмір файлу, розмір зображення, рівень компресії, яскравість, насиченість і різкість. Для структурування взаємозв'язків між зазначеними параметрами використано конструкції логіки предикатів. Встановлено, що окремі фактори можуть здійснювати як прямий, так і опосередкований вплив на інші елементи. Сформовано таблиці для представлення зв'язків за кожним фактором. Побудовано ієрархічні дерева безпосередніх і опосередкованих впливів та залежностей. Наведено приклад ієрархічних дерев для одного з факторів виокремленої множини. На основі аналізу структури зв'язків здійснено ранжування факторів якості. Для цього пораховано кількість зв'язків кожного типу, введено відповідні вагові коефіцієнти. При цьому позитивні значення ваг відповідають впливам, а від'ємні – залежностям. Обчислено оцінки важливості факторів. Проведено нормалізацію значень для перенесення шкали у позитивну область. Здійснено підсумкове оцінювання з врахуван-ням коефіцієнта нормалізації значень. Визначено ранги факторів та відповідні рівні пріоритетності. Вхідні дані та результати ранжування представлено у табличному вигляді. Розроблено модель, що відображає рівні пріоритетів факторів впливу на якість растрових зображень. Отримані результати можуть бути використані для оцінювання якості зображень на основі методів нечіткої логіки та машинного навчання з подальшим розробленням відповідної нечіткої системи.

Ключові слова: ранжування, фактор, пріоритет, растрове зображення, оцінювання якості, модель пріоритетного впливу, зв'язок між факторами, прямий вплив, опосередкований вплив.

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