Information system for determining the priority of digital image quality factors*

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Abstract

The quality of digital images is determined by a set of factors, among which the key ones are resolution, color depth, color model, file format, file size, image size, compression, brightness, saturation, and sharpness. The paper presents a developed semantic model that represents the relationships between factors. Reachability matrices are formed for direct and indirect relationships. The rank and weight of each factor are determined. The calculation results are presented in a tabular format. The obtained results of the factor ranking confirm the hypothesis of the unequal influence of various parameters on the final quality of digital images and substantiate the feasibility of using the ranking method to determine the factor priority. An information system is developed to determine the factor priority using the ranking method based on semantic networks and reachability matrices. It provides a full cycle of analysis from input of primary data to visualization of final results. The constructed algorithm is implemented by software tools in the Python language using modular architecture and a graphical user interface. The experiment shows that the highest priority is given to parameters such as color model, file format, and resolution, while file size and sharpness have the lowest impact. The proposed system provides a comprehensive analysis and can be used to make informed decisions when processing and using digital images in various fields.

Keywords

Digital image, information system, quality factor, semantic network, ranking method, factor priority, image quality [1]

1. Introduction

A digital image is a discrete form of visual information presentation based on a matrix representation of a signal in the form of pixels with certain numerical values of brightness and color. Its creation involves the discretization and quantization of a continuous visual signal, which provides the ability to store, transmit and algorithmically process data with a high level of reproducibility [1–3]. The main influence on the quality of digital images is exerted by such factors as resolution, color depth, color model, file format, file size, image size, brightness, saturation, sharpness.

Resolution determines the number of pixels in an image or the density of pixels per unit area. High-resolution images contain more information about small structures. High resolution is especially important in areas where small details are of great importance (medical diagnostics, security, video production, etc.) [4]. Color depth determines the number of color shades that can be encoded in each pixel. Increasing the color depth enhances the number of possible gradations of each channel brightness, i.e. the range of reproducible colors and the smoothness of their transitions. This allows one to capture tone differences and avoid rapid posterization [5]. The term "color model" should be understood as a way to represent colors in digital images, usually through

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coordinates in a selected color area. The most common color models are RGB, CMYK, HSV/HSL, LAB [6]. The image file format determines the way the data is encoded and compressed. Some formats (e.g. PNG, TIFF) use lossless compression or store data without loss at all, while others (JPEG, WebP, etc.) use lossy algorithms. Lossy compression reduces the file size by removing subtle details, but can degrade the quality at high compression levels [7]. The file size of an image (number of bytes) is directly related to its size, resolution, and color depth [8]. The image size usually refers to its dimensions in pixels. The details also depend on this: images with more pixels capture more information. Thus, the optimal image size is selected according to the context: a larger size allows one to see fine details, but requires more memory and processing time [8, 9]. Brightness characterizes the level of the image illumination. A standard brightness balance allows one to convey details in both bright and dark areas. If the brightness is insufficient, the shadows become excessively dark and the details are lost. If the brightness is excessive, "burned out" areas appear with the information loss [10]. Saturation describes how bright and "pure" the color is in the image. Insufficient saturation makes the image light and less informative, while excessively high saturation can cause oversaturation and color distortion. Balanced saturation provides naturalness and expressiveness of color, which positively affects the perception of the image quality [10, 11]. The image sharpness is the clarity degree of textures and contours of various details, which affects the information perception [12, 13].

Modern research indicates that digital images are the basis for the functioning of computer vision systems [14], automated object classification and segmentation [15, 16], as well as intelligent data analysis systems [17]. Their quality determines the accuracy and reliability of the processing results. The quality of digital images is influenced by many factors, prioritizing of which contributes to improving the information presentation, which indicates the relevance of the research conducted, the main goal of which is to develop an information system for analyzing relationships between factors and determining priorities using the ranking method. At the same time, the main tasks for achieving this goal are: developing a semantic model of relationships between factors of the digital image quality, constructing a reachability matrix of factors, determining the factor priority using the ranking method, developing an algorithm for the operation of an information system to determine the factor priority, and implementing this system.

2. Literature review

A number of modern scientific works are devoted to the image processing and the study of factors affecting its quality. In [18], a multi-scale image quality transformer MUSIQ is presented, which processes illustrative material in native dimensions and allows capturing quality at different scales. The model is also able to capture the image quality with different degrees of detail. However, MUSIQ presents an integral quality assessment without explicit decomposition into individual factors.

The study [19] is devoted to the non-reference assessment of the image quality based on Swin-Transformer statistics and natural scene. The model performs multi-scale feature extraction and uses a function improvement module. Natural scene statistics compensate for the information loss caused by the image size changes. The advantage of such solutions is the effective aggregation of local and global information, which increases the stability of predictions on heterogeneous distortions. The disadvantage is the low interpretability of the results without presenting cause-and-effect relationships between factors.

An important study [20] is devoted to a systematic analysis of current approaches to the quality assessment of medical images. The authors summarize 42 studies and compare the image assessment methods. They note that high-quality images provide improved visibility of anatomical structures, anomalies and lesions, which leads to more accurate diagnosis. At the same time, noise, resolution problems and artifacts are identified as the main problems of the image quality. The need to develop consistent assessment procedures is indicated to improve diagnostic outcomes and patient care.

Human perceptual factors (age, experience, viewing context, content genre) are important modulating variables in the quality interpretation, as evidenced by experimental studies [21].

Single- and two-factor studies [22–24] (e.g., detailed analysis of the effects of blur [22], brightness and structural characteristics [23], resolution and sharpness [24]) provide a deep understanding of the influence mechanisms of individual characteristics and allow the creation of specialized quality indicators for specific tasks. However, a narrow focus does not ensure the assessment completeness. Instead, the use of multi-criteria analysis methods makes it possible to identify cause-and-effect relationships between factors [25, 26]. In addition, methods aimed at increasing the generalizability of quality representations and multitask approaches demonstrate that additional related tasks (defect detection, semantic features, linguistic representations) can significantly improve the quality of predictions [27, 28].

3. Material and methods

Visualization of relationships between factors is carried out using modeling based on the theory of semantic networks. The conceptual essence of semantic networks is to represent a complex subject area in the form of a structure formed by sets of nodes and arcs. Nodes correspond to individual concepts or objects (in this case, digital image quality factors), and arcs denote the relationship between them. Each relationship has a clearly defined semantic load, which sets its semantic interpretation. That is, semantic networks provide the possibility of a comprehensive analysis of interdependencies between concepts. Let $X=\{x_1, x_2, \ldots, x_n\}$ be a set of factors to be analysed. Each factor x_i represents a certain parameter or characteristic that can affect the image final quality. The semantic network is presented in the form of a directed graph $G=(V, E)$, where the set of vertices V corresponds to the set of factors X, i.e. $V=X$. Thus, each node of the graph is equivalent to a specific factor. The set of arcs E represents all existing relationships between factors. The existence of the arc $e=\{x_i, x_j\}\in E$ means that factor x_i influences factor x_j or, on the contrary, it is in a relationship of dependency with it [25, 26].

Based on the relationships between factors, the reachability matrix $M=[m_{ij}]$ is constructed. The reachability matrix is square, and the rows and columns correspond to the ordered set of factors $X=\{x_1, x_2, \ldots, x_n\}$. The element m_{ij}, located at the intersection of the corresponding row and column (i, j), represents the fact of the presence or absence of a reachability relationship from one factor to another. If the relationship exists, one is written, if it is absent, then zero is indicated. In this case, the main diagonal is always filled with ones, which represents the fundamental property of reflexivity: each factor has a reachability relationship with itself [25, 28, 29].

The factor importance (priority) is determined by the ranking method. Four subsets are formed: direct influences, indirect influences, direct dependencies and indirect dependencies. The number of relationships of each type is denoted as h_1, h_2, h_3, h_4. Then the influences have a positive value, because they enhance the factor significance. Dependencies are interpreted as negative values, because they reduce its autonomy. It is natural to assume that by module, the weights of influence and dependency are the same [29, 30]. Let the weight values for influences and dependencies be as follows: $w_1=10, w_2=5, w_3=-10, w_4=-5$, The final weight of each factor is determined by the sum of all four components:

$$X_{ij}=\sum_{i=1}^{4}\sum_{j=1}^{n} h_{ij} w_i . \quad (1)$$

Since some of the coefficients have positive values $(w_1>0, w_2>0)$, and some have negative values $(w_3>0, w_4>0)$, there is a need to shift the scale to the positive area. This is achieved by normalization using the formula:

$$\Delta_j = max|X_{3j}| + max|X_{4j}|, (j = 1, 2, \ldots, n). \tag{2}$$

Taking into account the expressions (1) and (2), the final formula for calculating the weight values of factors is as follows:

$$X_{Fj} = \sum_{i=1}^{4} \sum_{j=1}^{10} (x_{ij} w_i + \Delta_j). \tag{3}$$

The factor that receives the highest weight value corresponds to the highest rank R_j. The factor priority P_j is interpreted as the inverse of the rank. That is, the rank with the highest value corresponds to the first priority [25, 28].

4. Experiment, results and discussion

The main factors affecting the quality of digital images are: X_1 — resolution, X_2 — color depth, X_3 — color model, X_4 — file format, X_5 — file size, X_6 — image size, X_7 — compression, X_8 — brightness, X_9 — saturation, X_{10} — sharpness. The specified factors form the following set: $X = \{X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}\}$. The relationships between the factors are demonstrated using the developed semantic network (Fig. 1).

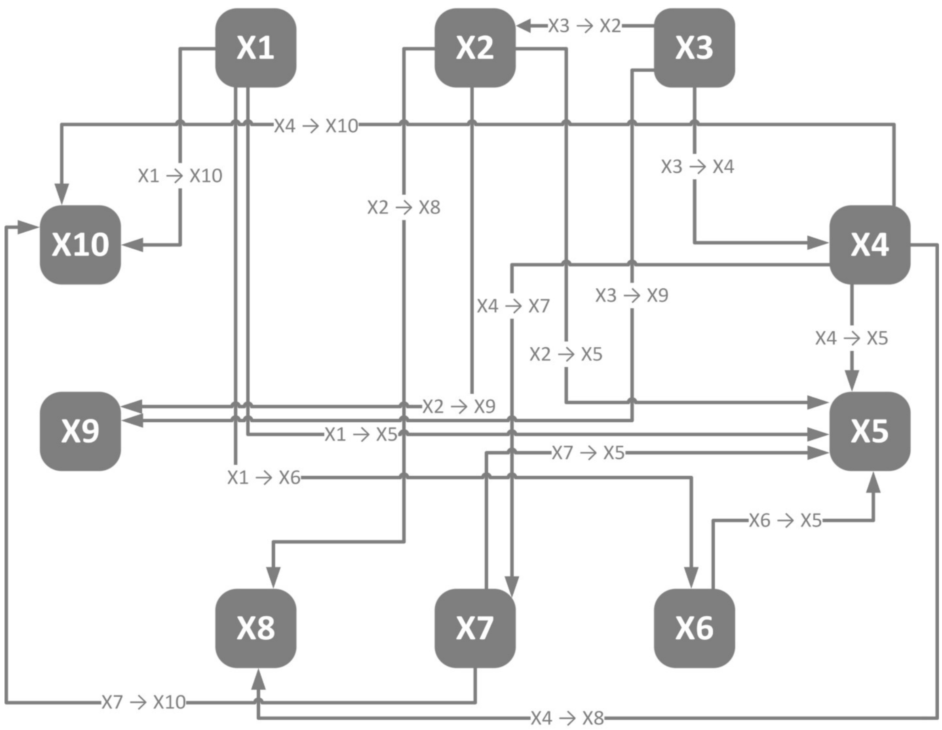

Figure 1: Semantic network of factors affecting the quality of digital images.

According to the semantic network (Fig. 1) reachability matrices are developed: M_1 is a matrix of direct relationships, M_2 is a matrix of indirect relationships.

$$M_1 = \begin{bmatrix} 1000110001 \\ 0100100110 \\ 0111000010 \\ 0001101101 \\ 0000100000 \\ 0000110000 \\ 0000101001 \\ 0000000100 \\ 0000000010 \\ 0000000001 \end{bmatrix}, M_2 = \begin{bmatrix} 1000100000 \\ 0100000000 \\ 0010101111 \\ 0001100001 \\ 0000100000 \\ 0000010000 \\ 0000001000 \\ 0000000100 \\ 0000000010 \\ 0000000001 \end{bmatrix}.$$

The next stage of the experiment is to calculate the factor ranks and determine the corresponding priority levels. The results of the calculations are presented in a tabular format (Table 1). Table 1 contains 12 columns: factor (factor number), h_{1j} is the number of direct influences on the analyzed factor; h_{2j} is the number of 2nd-order influences (indirect); h_{3j} is the number of direct dependencies; h_{4j} is the number of 2nd-order dependencies; X_{1j}, X_{2j}, X_{3j} and X_{4j} are calculated according to the expression (1); X_{Fj} characterizes the overall assessment of factors taking into account all categories of relationships and the corrective mechanism and is calculated according to the formula (3); the factor rank represents its number in the overall rating, where rank 1 corresponds to the lowest priority; the factor priority is the inverse of the rank and indicates the factor importance.

Table 1
Ranking of factors affecting the quality of digital images

Factor j	h_{1j}	h_{2j}	h_{3j}	h_{4j}	X_{1j}	X_{2j}	X_{3j}	X_{4j}	X_{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

Taking into account the theoretical principles of the ranking method presented in Section 3 and the experimental results, an information system algorithm is developed to determine the factor priority (Fig. 2).

The information system for determining the factor priority by the ranking method is implemented using the object-oriented programming paradigm in the Python language. It provides a full cycle of analysis from input of primary data to visualization of final results. The software has a clearly structured modular architecture. The main class implements the Model-View-Controller pattern, where the data model is represented by internal structures for storing the information about the number of relationships for each factor and the calculation results. The presentation is carried out using a graphical user interface based on the Tkinter library. The controller provides the coordinated interaction between the software components.

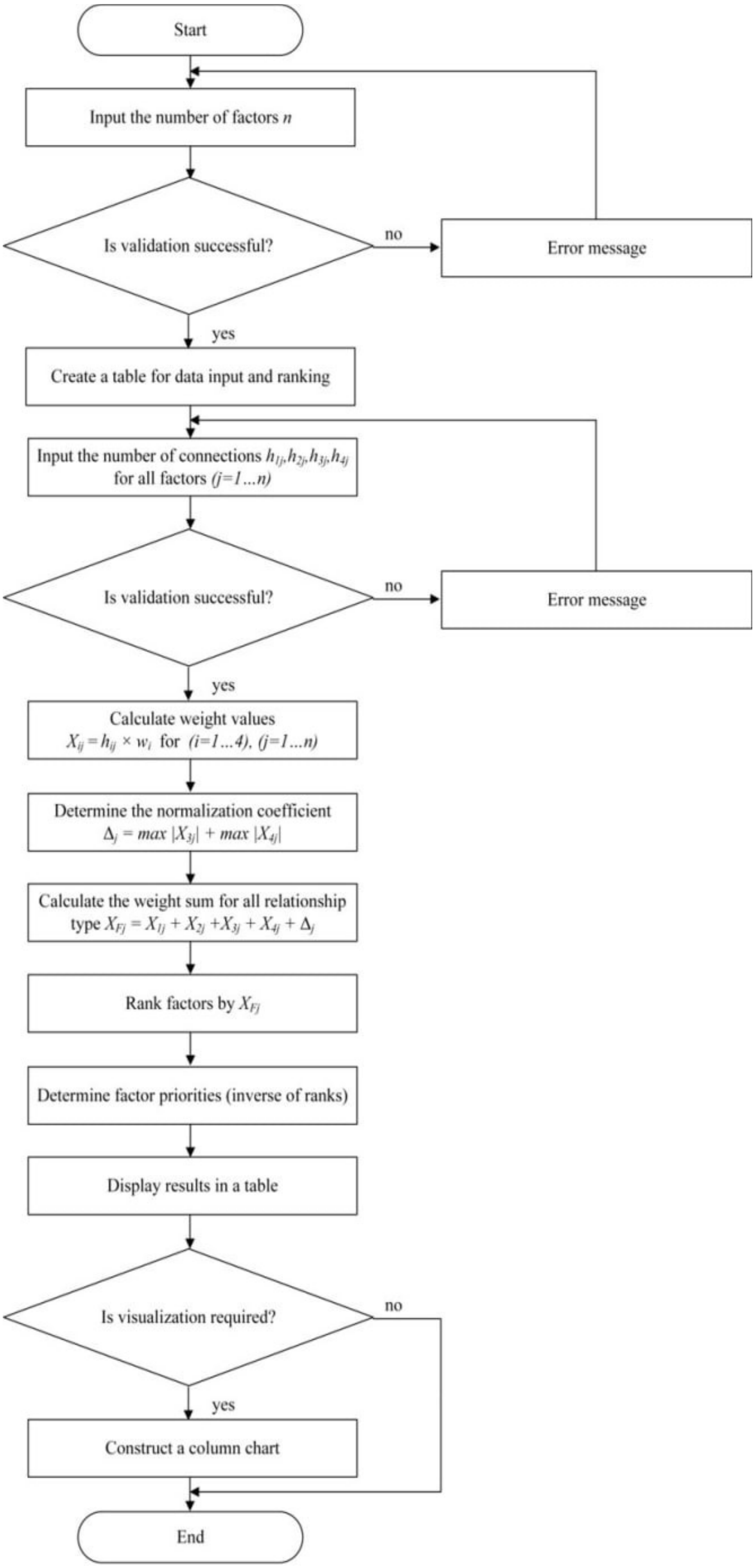

Figure 2: System algorithm for determining the factor priority.

The interface contains a parameter input component. Input data validation and warning about possible input errors are performed. The dynamic table automatically adapts to the number of input factors. The navigation between input fields is carried out using an extended system of keyboard shortcuts. The calculation module contains an input data validator that checks the correctness of the input values and their compliance with the mathematical requirements of the algorithm.

The ranking and priority determination module provides sorting of factors by the value of the integral indicator and assigning the corresponding ranks and priorities. The visualization module includes a statistical diagram generator using the Matplotlib library. The adaptive scaling system automatically adjusts the visualization parameters depending on the factor number. Logarithmic scaling of the diagram width and dynamic calculation of the caption rotation angle are performed.

The software interface with an example of determining the priority of digital image quality factors is presented in Fig. 3.

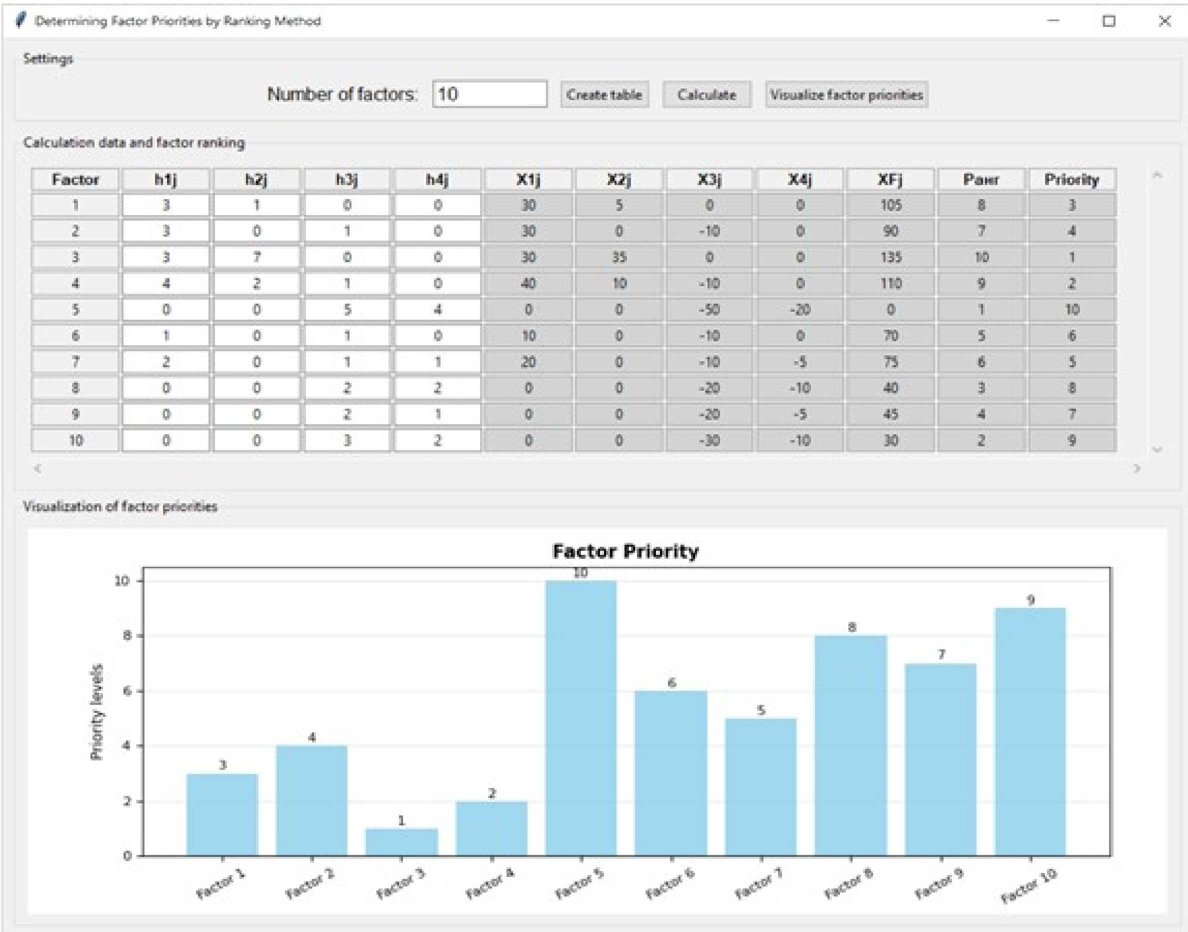

Figure 3: Interface of the system for determining the factor priority.

The user enters the required number of factors and clicks "Create a table" button. If the data is entered incorrectly, an error message appears. Logically, it is allowed to enter an integer greater than zero. If the data is entered correctly, a table is created. The user enters data on the number of relationships in columns h_1, h_2, h_3, h_4 and clicks "Calculate" button. At the next stage, the user can click "Visualize factor priority" button to display a column chart. In this case, the ordinal numbers of the factors are presented on the abscissa axis, and the priority levels are on the ordinate axis.

The developed software product can be used in decision-making under conditions of uncertainty and incomplete information.

The obtained results of the factor ranking confirm the hypothesis of unequal influence of different parameters on the final quality of digital images and substantiate the feasibility of using the ranking method to determine the factor priority.

The constructed semantic network (Fig. 1) makes it possible to formalize the complex relationships between parameters that are traditionally considered separately. This provides a systematic understanding of their contribution to the final quality. It is found that the dominant role is played by the color model, which determines the way color information is represented in the image and directly affects the ability to reproduce shades and transmit visual details.

The second and third places in importance are the file format and resolution, which correlates with the results of previous studies in the area of computer vision and digital processing [4, 7]. It is these parameters that most often determine the image suitability for further analysis or use in critical applications (for example, in medical diagnostics or security systems). Factors characterizing color depth, compression, image size, saturation, and brightness receive intermediate positions in the formed hierarchy. This indicates their importance for subjective perception and quality assessment. However, they are inferior to the fundamental parameters of data encoding and reproduction. Sharpness and file size demonstrate the lowest priority. This result indicates that these factors are rather derived characteristics that do not determine the image essence.

The developed algorithm (Fig. 2) and its software implementation in the form of an information system (Fig. 3) demonstrate the efficiency of the transition from a theoretical model to an interactive analysis tool. The integration of visualization modules makes it possible not only to obtain numerical estimates, but also to present the results in a visual form, which simplifies the interpretation for users. Compared with existing non-reference methods for quality assessment [18, 19, 22], the proposed approach is characterized by higher interpretability, since it provides clear tracking of cause-and-effect relationships between parameters.

5. Conclusions

The study presents a comprehensive ranking of ten key factors that determine the quality of digital images. To formalize the system of interdependencies between resolution, color depth, color model, file format and size, geometric image parameters, compression level, brightness, saturation and sharpness, a hierarchical structure of influences and dependencies is constructed in the form of semantic networks and reachability matrices. This allows one to clearly represent the relationship between the characteristics and transform them into a quantitative form for further analysis.

Based on the ranking results, a hierarchy of the factor priority is established. The most significant factor that has the greatest impact on the digital image quality is determined to be the color model $(R_j = 10; P_j = 1)$, while the lowest significance is demonstrated by the file size $(R_j = 1; P_j = 10)$. The results represent a consistent set of weight values and provide a holistic view of the role of each parameter in the image reproduction. The obtained data can be used in further scientific research and practical applications that require improving the digital image quality.

To implement the proposed approach, an information system for determining the factor priority is developed, which automates the process from data input to result visualization. The system is developed using the object-oriented programming paradigm in the Python language and contains three main modules: settings, calculated data and factor ranking, visualization of factor priority.

At the same time, the study has certain limitations related to the possible subjectivity of the expert assessments at the stage of determining the set of factors and formalizing their relationships.

Further research can be aimed at refining the weight coefficients using multi-criteria optimization and expanding the model by introducing additional parameters and linguistic descriptions of relationship types.

The practical significance of the development is to create a ready-made tool for determining the priority of digital image quality factors, which can be used in computer vision systems, automated image processing procedures, as well as in industries where it is necessary to make informed decisions about improving visual data. In addition, this system is a universal tool and can be used to determine the importance of factors in any technological process.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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