

Image Compression via Nonlinear Multiscale Decomposition with Fractional-Rational Approximation

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Abstract: Currently, image compression algorithms are an integral part of modern information systems in various industries and spheres of human activity, including telecommunications, medicine, artificial intelligence, and defense technologies. This paper deals with a novel image compression method based on nonlinear multiscale decomposition with fractional-rational approximation, providing a compact representation of image components while preserving reconstruction quality. The proposed algorithm consists of five steps, including image preprocessing, discretization, nonlinear multiscale decomposition, quantization, and arithmetic compression. The method was evaluated using 1000 test images and demonstrated an average compression ratio of 13.2, with reconstructed image quality of 41.5 dB,

outperforming classical wavelet-based approaches under comparable conditions (approximately by 8-10% on average). The computational complexity of the proposed algorithm remains suitable for practical implementation, making it a promising solution for efficient image compression in modern digital systems.

Index Terms: Digital Compression, Nonlinear Method, Wavelet Analysis, Nonlinear Multiscale Decomposition, Aerial Photograph Compression.

1. Introduction

Today, image compression algorithms are an integral part of modern information systems in various industries and spheres of human activity – from telecommunications and medicine to artificial intelligence and defense technologies. The development of information technology has led to a rapid growth in the volume of multimedia information, making image compression a critically important component of digital systems across various industries [1, 2]. The main areas of application of image compression methods are:

1. Telecommunications and network services. The application of image compression methods can increase the bandwidth utilization of communication channels, reduce data transmission delays, and improve the quality of service. Image compression is very important for mobile networks with high load and a large number of subscribers, network services, and cloud platforms, where compression efficiency affects the access speed and service stability [3, 4, 5, 6].

2. Satellite and unmanned aerial systems (UAS). Image compression is necessitated by limited bandwidth of communication channels, energy resources, and high requirements for data processing efficiency. In satellite systems, such image processing allows for the efficient transmission of large arrays of Earth remote sensing data [7, 8]. In UAS, image compression methods are a prerequisite for reducing delays in streaming video transmission, ensuring stable system control, and reducing the load on onboard systems. Such adaptive and intelligent image processing methods are important, which can vary compression parameters depending on flight conditions, communication channel quality, and computing resources, thereby contributing to increasing the reliability of onboard radio systems [9, 10, 11, 12].

3. Medicine. These methods play a key role during the storage and transmission of diagnostic data (MRI, CT, X-ray, ultrasound images) over medical computer networks [13, 14].

4. Computer vision and artificial intelligence systems. Image compression methods are the basis for optimizing the storage of training samples, reducing computing power, and accelerating data transfer between nodes of computing systems [15]. Compression algorithms can be directly included in the structure of neural networks, which will allow combining the tasks of encoding and pattern recognition into one whole.

5. Industrial Internet of Things (IIoT) and edge computing. IIoT systems are characterized by the use of high-resolution video cameras for individual nodes, which creates large data streams. Image compression enables the reduction of the load on the network infrastructure by decreasing the amount of transmitted information [16]. Adaptive compression algorithms in edge platforms contribute to the implementation of the concept of smart manufacturing of Industry 4.0 [17].

6. Digital twins. In the concept of digital twins, visual data is used to synchronize physical processes with their virtual models. Data compression creates the prerequisite for the ability to predict failures, optimize technological processes, and support management decisions [1].

7. Imaging radar. Compression algorithms are important at various stages of processing wideband signals and images in numerous radar applications [18], including radar meteorology [19, 20].

Therefore, image compression methods are an integral part of Industry 4.0. The application of these methods can ensure scalability, adaptability, and efficiency of intelligent processing of visual data [21].

Digital compression is a flexible technology, since the levels of used coding complexity and the degree of compression can vary according to the programs. The main principle of digital compression is the use of the so-called redundancy of the audio or video signal. Redundancy is explained by the fact that audio and video contain areas with similar characteristics. Thus, the entire information flow can be conditionally divided into a predictable part (in other words, redundancy) and a new, unpredictable part (known in information theory as entropy). The sum of these two quantities gives a data stream, the reduction of which will depend on how well we can make the “prediction”. Theoretically, it is possible to completely eliminate the redundancy and leave only the entropy, but this would require an ideal compression algorithm, which would be extremely complex and would take an unreasonably long time. If the degree of compression is so high that the resulting data stream rate becomes less than the entropy, then information is lost. In practice, the compression ratio is chosen less than the ideal one to provide some margin of reliability. This makes it possible to use simpler algorithms and perform repeated restoration/compression without noticeable loss of quality. In household equipment, the compression ratio can be higher than in studio equipment, and if multiple re-recording is not required, then some part of the entropy is discarded during the compression process [22].

Wavelet analysis provides the possibility of fairly efficient compression of photographic images and their restoration with small losses of quality, as well as solving filtering problems [23, 24]. Wavelet analysis is a special type of linear transformation of signals and physical data about the processes and physical properties of natural environments and objects reflected by these signals [25]. Wavelet basis functions allow one to focus on certain local features of the analyzed processes that cannot be detected using traditional Fourier and Laplace transforms. One of the main and especially fruitful ideas of wavelet representation of signals at different levels of decomposition is the division of signal approximation functions into two groups:

- approximating – coarse, with a sufficiently slow time dynamics of changes.
- detailing – with local and fast dynamics of changes against the background of smooth dynamics, with their subsequent fragmentation and detailing at other levels of signal decomposition (multi-scale or multi-scale analysis).

2. Analysis of Recent Research and Publications

Wavelet analysis is a widely used tool that can be used in fields of time series analysis, image processing, pattern recognition, remote sensing, and others. Originating from Haar's pioneering work and further developed through the contributions of Mallat, Meyer, Daubechies, Morlet, and others, it gives the possibility for efficient signal representation and processing across multiple temporal and spatial scales, making it particularly suitable for image compression and feature extraction. In the modern literature, the discrete wavelet transform is constructed using multiscale analysis [26, 27]. Multiscale analysis provides a natural basis for understanding wavelet bases and for constructing new examples. The history of the formulation of the concept of multiscale analysis is a great example of how programs stimulate theoretical research. Mallat first heard of Meyer's bases while working on image analysis, in which the idea of studying images simultaneously at different scales and comparing the results had been popular for many years. This prompted him to consider orthonormal wavelet bases as a tool for mathematically describing the "information gain" required to go from a coarse approximation to a higher resolution approximation. This understanding crystallized into the concept of multiscale analysis [28, 29]. Burt and Adelson established the foundations of multiscale image representation by decomposing images into Gaussian and Laplacian pyramids, an approach that later evolved into wavelet-based multiscale analysis [30]. By storing the coarse image representation and the detail components at each scale, this method gives the possibility for efficient image compression while preserving high reconstruction quality.

Today, there is a large number of publications in the scientific literature in the field of image compression. In the article [31], modern and specialized image compression methods are considered. These methods are focused on increasing the coding efficiency taking into account the specifics of various industries. The article explores classical and new approaches to image processing for medical, scientific and technical applications. Special attention is paid to the trade-off between compression ratio, computational complexity and preservation of visual and structural quality.

In the article [32], a comprehensive review of modern image compression methods is performed, with an emphasis on classical algorithms and Region of Interest (ROI)-oriented approaches. The authors analyze the efficiency of various compression strategies from the standpoint of preserving informatively important image areas and reducing the total data volume. The advantages of ROI-oriented methods in the fields of medicine, security, and computer vision are shown.

Articles [33, 34, 35] are devoted to a comprehensive analysis of the current trends in the development of image processing and compression methods in the context of deep learning and quantum computing. The authors of the articles state that current trends in the development of image compression methods are formed at the intersection of deep learning, specialized application solutions, and quantum technologies. This, in turn, provides an opportunity to create highly efficient, adaptive, and context-oriented image compression methods that can meet the requirements of the next generation of information systems.

Studies [36, 37, 38, 39] consider fundamental aspects of signal processing, radar data monitoring, and image compression standards that form the theoretical and methodological basis for modern information compression systems.

Nowadays, image compression methods mainly use three main approaches: classical transformation-based compression, video-oriented methods, and deep learning. In parallel, modern standards for image and video coding are being improved, in particular VVC, which provide high compression efficiency through the use of complex prediction and transformation algorithms. However, such approaches are characterized by significant computational complexity, require large amounts of training data or long-term optimization, which limits their application in systems with limited computing resources [40, 41, 42]. Under these conditions, multiscale image representation methods remain a promising alternative due to their relatively low computational complexity and ability to effectively preserve image details. At the same time, most existing multiscale compression methods are based on fixed transformations and do not sufficiently take into account the nonlinear features of local image structures, which limits their effectiveness.

In article [40], a comprehensive review of modern deep learning-based image compression methods is provided, including neural networks, transformer, and generative models. The authors show that such approaches provide better speed-to-distortion performance, but require significant computational resources and large training samples. In [41], a critical analysis of modern deep neural architectures for image compression is performed, their advantages and

disadvantages compared to classical methods are considered. Particular attention is paid to the trade-off between compression efficiency, model complexity, and hardware resource requirements. In [42], the authors proposed an adaptive compression method that takes into account the content of individual image regions by using content-oriented bit allocation. Article [43] proposes a compression model combining frequency analysis with attention mechanisms for more efficient representation of textural details. The paper [44] is devoted to the application of deep learning to compress satellite images in infrastructure monitoring tasks. The results show that neural models provide high compression efficiency while preserving important spatial information necessary for further analysis. The paper [45] presents a modern overview of end-to-end image compression methods and analyzes the development trends of neural coding, including neural networks, transformers, and JPEG AI. The authors note that despite significant progress in achieving high compression efficiency, the problems of computational complexity of such algorithms remain relevant.

The JPEG2000 standard is one of the most common image compression methods and is based on the discrete wavelet transform [46, 47]. In contrast to the conventional JPEG format based on the cosine transform, JPEG2000 enables better image quality at high compression ratios. The main advantage of this standard is scalability and high reconstruction quality, but the method requires high computational complexity.

The HEVC-based (High Efficiency Video Coding) compression standard is currently actively used for image compression [48, 49]. This standard also has high efficiency due to more complex block prediction and improved entropy compression methods. However, the disadvantage of this standard is computational complexity, including during decompression.

Standards based on deep learning compression models are constructed on the principle of the use of autoencoders, convolutional neural networks, and transformers [50, 51]. These approaches allow to achieve high compression efficiency compared to classical standards at low bitrates. However, the main disadvantage is the long learning process.

Therefore, the review of scientific sources and applied directions demonstrates that image compression methods have evolved from classical coding algorithms to intelligent, adaptive, and semantically oriented approaches integrated with deep learning, cyber-physical systems, and Industry 4.0 technologies.

The scientific novelty of this research is the development of image compression method based on nonlinear multiscale decomposition using fractional-rational approximation, which provides a more flexible and adaptive representation of local image structures. The difference of the proposed approach from classical wavelet methods, which are based on linear transformations with fixed basis functions, is the accurate description of sharp transitions and textural features of images. These properties allow forming a sparser signal representation and increasing the efficiency of quantization and coding.

3. The Synthesis of Image Compression Method

In order to improve the quality of aerial photo compression, we propose to develop a multiscale analysis using nonlinear approximation of discrete values of the pixel matrix of the initial image. Linear, especially linear polynomial, approximation often does not correspond to the nature of the function. For example, a high-degree polynomial grows rapidly at $|x| \rightarrow \infty$; therefore, even a simple function $y(x) = \frac{1}{(1+x^2)}$ is poorly approximated by a polynomial on a large segment. Since the approximation is performed in a wide range of argument changes, the use of nonlinear dependence on coefficients is even more advantageous here than in interpolation.

The main idea is as follows. Multiscale analysis consists of a sequence of approximation spaces V_j . More precisely, closed subspaces V_j satisfy the inclusion:

$$\dots \subset V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2} \subset \dots \quad (1)$$

where

$$\overline{\bigcup_{j \in \mathbb{Z}} V_j} = L^2(R) \quad (2)$$

$$\bigcap_{j \in \mathbb{Z}} V_j = \{0\} \quad (3)$$

If we denote by P_j the orthogonal projection operator on V_j , then it is guaranteed that $\lim_{j \rightarrow \infty} P_j f = f$ for all $f \in L^2(R)$. There are many chains of spaces satisfying equations (1) – (3) that are not related to “multi-scaleness”. Multi-scaleness is a consequence of the additional requirement:

$$f \in V_j \Leftrightarrow f(2^j \cdot) \in V_0 \quad (4)$$

All these spaces are scaled versions of the central space V_0 . Another property required by multi-scale analysis is invariance V_0 under integer shifts:

$$f \in V_0 \Rightarrow f(\cdot - n) \in V_0 \text{ for all } n \in \mathbb{Z}. \quad (5)$$

Together with equation (4) this implies $f(\cdot - 2^j n) \in V_j$ for all $n \in \mathbb{Z}$, if $f \in V_j$. Finally, it is required that there exists $\varphi \in V_0$ such that:

$$\{\varphi_{0,n}; n \in \mathbb{Z}\} \text{ is an orthonormal basis in } V_0, \quad (6)$$

where for all $j, n \in \mathbb{Z}$, $\varphi_{j,n}(t) = 2^{-j/2} \varphi(2^{-j}t - n)$. Usage of equations (6) and (4) lead to the fact that $\{\varphi_{j,n}; n \in \mathbb{Z}\}$ is an orthonormal basis in V_j for all $j \in \mathbb{Z}$. In the literature φ is often called the “scaling function” of multi-scale analysis.

The basic principle of multiscale analysis is as follows: for any set of closed subspaces satisfying equations (1) – (6), there exists such an orthonormal wavelet basis $\{\psi_{j,k}; j, k \in \mathbb{Z}\}$ for $L^2(\mathbb{R})$, where $\varphi_{j,k}(t) = 2^{-j/2} \varphi(2^{-j}t - k)$, that for all of f from $L^2(\mathbb{R})$:

$$P_{j-1}f = P_jf + \sum_{k \in \mathbb{Z}} \langle f, \psi_{j,k} \rangle \psi_{j,k} \quad (7)$$

where P_j is orthogonal projection onto V_j . Moreover, the wavelet ψ can be constructed explicitly. Let us see how this can be done.

For each $j \in \mathbb{Z}$, we define W_j as the orthogonal complement of V_j in V_{j-1} . We have:

$$V_{j-1} = V_j \oplus W_j \quad (8)$$

$$W_j \perp W_{j'}, \text{ if } j \neq j'. \quad (9)$$

If $j > j'$, for example, then $W_j \subset V_{j'} \perp W_{j'}$.) Accordingly, for $j < J$

$$V_j = V_J \oplus \bigoplus_{k=0}^{J-j-1} W_{J-k} \quad (10)$$

in which all subspaces are orthogonal. Since we use equations (2) and (3), then:

$$L^2(\mathbb{R}) = \bigoplus_{j \in \mathbb{Z}} W_j, \quad (11)$$

this means decomposition $L^2(\mathbb{R})$ into mutually orthogonal subspaces. Moreover, the spaces W_j follow from V_j and the scaling property (4):

$$f \in W_j \Leftrightarrow f(2^j \cdot) \in W_0 \quad (12)$$

Formula (7) is equivalent to the statement that for a fixed j the family $\{\psi_{j,k}; k \in \mathbb{Z}\}$ forms an orthonormal basis in W_j . Having equations (11), (2), (3), we automatically obtain that the entire set $\{\psi_{j,k}; j, k \in \mathbb{Z}\}$ is an orthonormal basis for $L^2(\mathbb{R})$. On the other hand, equation (12) guarantees that if $\{\psi_{0,k}; k \in \mathbb{Z}\}$ is an orthonormal basis in W_0 , then $\{\psi_{j,k}; k \in \mathbb{Z}\}$ will be an orthonormal basis in W_j for any $j \in \mathbb{Z}$. Thus, our problem is reduced to finding such $\psi \in W_0$, that functions $\psi(\cdot - k)$ form an orthonormal basis in W_0 .

Multiscale decomposition. Consider a signal as a sequence of numbers $x = \{x_n\}_{n=-\infty}^{n=\infty}$. For signal smoothing, noise suppression and other purposes, filters or convolution transforms of the form are often used:

$$y_n = \sum_k h_k x_{n-k} \quad (13)$$

The signal $y = \{y_n\}_{n=-\infty}^{n=\infty}$ is obtained by “local averaging” of the signal x using a set of “weights” $h = \{h_k\}$ (see Figure 1).

In this study, we need the following concepts [52, 53, 54].

1. Discrete Fourier transform (DFT) of the signal:

$$X(\omega) = \sum_n x_n e^{-i\omega n} \quad (14)$$

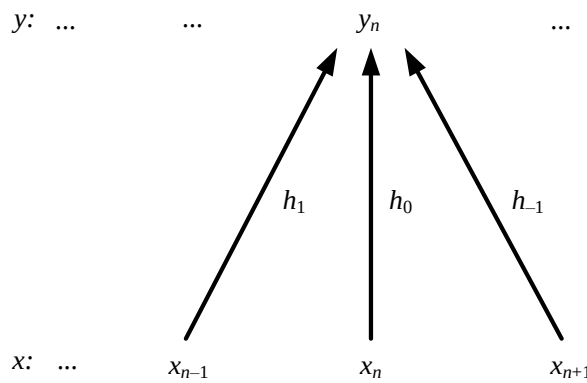


Fig. 1. Scheme of obtaining signal values.

2. z-transform of the signal:

$$X(z) = \sum_n x_n z^{-n} \quad (15)$$

3. The Fourier transform of the function $x(t)$ has the form

$$\tilde{x}(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} x(t) e^{-i\omega t} dt \quad (16)$$

In these terms, the application of the filter is written as follows:

$$Y(\omega) = H(\omega) X(\omega) \quad (17)$$

$$Y(z) = H(z) X(z) \quad (18)$$

If the signal is finite, it is usually defined periodically for all integer values of the index.

The transposed filter h^* consists of the same coefficients as the filter h , rearranged in reverse order. In the Fourier domain, the transposed filter has the form $\bar{H}(\omega)$. The coefficients of all signals and filters will be assumed to be real.

Subband decomposition. In this case, $|X(\omega)|$ characterizes the distribution of the “energy” of the signal over frequencies $\omega \in [-\tau, \tau)$. Sometimes it is useful to decompose the signal into components whose energy is concentrated in different frequency subbands (that is, significantly different from zero on various subsegments of the segment $\omega \in [-\tau, \tau)$), and encode them with different degrees of detail (for example, depending on the sensitivity of the human ear to sounds of different frequencies). Before the creation of wavelet analysis, the scheme that we will now describe was used for this.

We want to find two filters, h (suppressing high frequencies) and g (suppressing low frequencies), which would allow to decompose the signal into two components: $X_H(z)$ and $X_G(z)$; thin them out by half (half of the values

become redundant – after all, the frequency range has been halved), and then, using transposed filters, accurately restore the original signal from these data (this operation can be applied recursively). It is convenient to write the conditions for the desired filters in terms of z -transformations.

Let $Y(z)$ is the z -transformation of one of the components. Before encoding, it is thinned out by half, and before restoring the original signal, it is brought to the original length by inserting zeros between adjacent values. In this case, the z -transformation from the $Y(z)$ is transformed into $(Y(z) + Y(-z))/2$. Substitute here (17) for each of the filters, and we obtain z -transformations of the components before restoration.

$$X_H(z) \rightarrow (H(z)X(z) + H(-z)X(-z))/2 \quad (19)$$

$$X_G(z) \rightarrow (G(z)X(z) + G(-z)X(-z))/2 \quad (20)$$

z -transformations of transposed filters have the form $H(z^{-1})$ and $G(z^{-1})$. The signal is reconstructed with their help exactly if:

$$X(z) = \left[(H(z^{-1})H(z) + G(z^{-1})G(z))X(z)/2 + (H(z^{-1})H(-z) + G(z^{-1})G(-z))X(-z)/2 \right] \quad (21)$$

We obtain the conditions for perfect reconstruction:

$$H(z^{-1})H(z) + G(z^{-1})G(z) = 2 \quad (22)$$

$$H(z^{-1})H(-z) + G(z^{-1})G(-z) = 0 \quad (23)$$

In matrix form they are written as follows:

$$M(z)(M(z^{-1}))^* = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix} = 2\mathbf{E} \quad (24)$$

$$M(z) = \begin{bmatrix} H(z) & G(z) \\ H(-z) & G(-z) \end{bmatrix} \quad (25)$$

Substituting $z = e^{i\omega}$, we obtain the conditions for the DFT of the desired filters:

$$|H(\omega)|^2 + |G(\omega)|^2 \equiv 2 \quad (26)$$

$$\overline{H(\omega)}H(\omega + \pi) + \overline{G(\omega)}G(\omega + \pi) = 0 \quad (27)$$

Suppose that we have found h such that

$$|H(\omega)|^2 + |H(\omega + \pi)|^2 \equiv 2 \quad (28)$$

$$G(\omega) = -e^{-i\omega} \overline{H(\omega + \pi)} \quad (29)$$

The problem is reduced to the transformation of the trigonometric polynomial $H(\omega)$, which satisfies (28). We will dwell on the methods of constructing such polynomials in the next section. Filters h and g , which satisfy (27), are called quadrature mirror filters (QMF).

Exactly the same operation can be applied to one or both of the obtained components and to subsequent components, achieving the desired frequency localization [55, 56, 57]. This allows to adapt to the characteristics of the signal by choosing a suitable “decomposition tree”. It may look, for example, as in Figure 2.

Pyramid representation. Figure 3 schematically depicts a pyramid representation of a one-dimensional signal [36]. Two pyramids are associated with the signal: a Gaussian Pyramid (GP) and a Laplacian Pyramid (LP). These

names reflect the analogy with the popular operations in graphics of smoothing (convolutions with a bell-shaped filter) and separation of differences (calculation of the “discrete Laplace operator”). This construction can be considered a simplified version of the previous one.

At the base of the GP is the output signal. The next floor of the GP is the output signal, filtered by a low-pass filter h and then thinned by half – it is assumed that the filter h “kills” the upper half of the frequency range, so the sample density can be reduced accordingly. The same operation is applied to this floor, and so on. In the case of finite signals, each subsequent floor is half the length of the previous one.

Levels of the PL are the differences between consecutive levels of the GP. They are calculated as follows. Let, for example, g_1 and g_2 – the first and second floors of the PG, d_1 – the first floor of the LP that we want to calculate. To do this, first the lengths of the floors are equalized:

$$g_2 = \{\dots \quad g_2(k-1) \quad g_2(k) \quad g_2(k+1) \dots\} \mapsto \{\dots \quad g_2(k-1) \quad 0 \quad g_2(k) \quad 0 \quad g_2(k+1) \dots\}, \quad (30)$$

and then filtering is performed by a conjugate filter h^* (its coefficients are the coefficients of h , rearranged in reverse order, in the Fourier domain this is equivalent to the transition to $\bar{H}(\omega)$). As a result, a vector is obtained. $\tilde{g}_2$ By definition,

$$d_1 = g_1 - \tilde{g}_2 \quad (31)$$

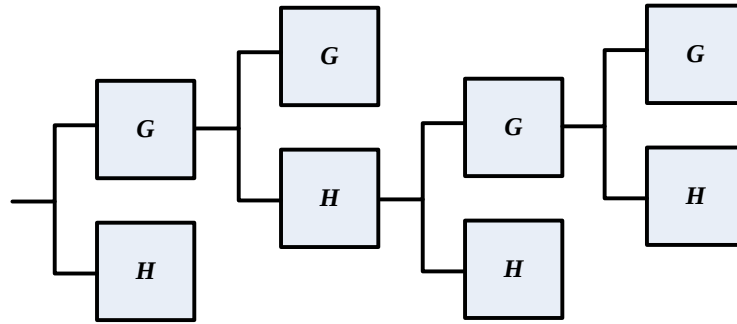


Fig. 2. “Decomposition tree” of the signal.

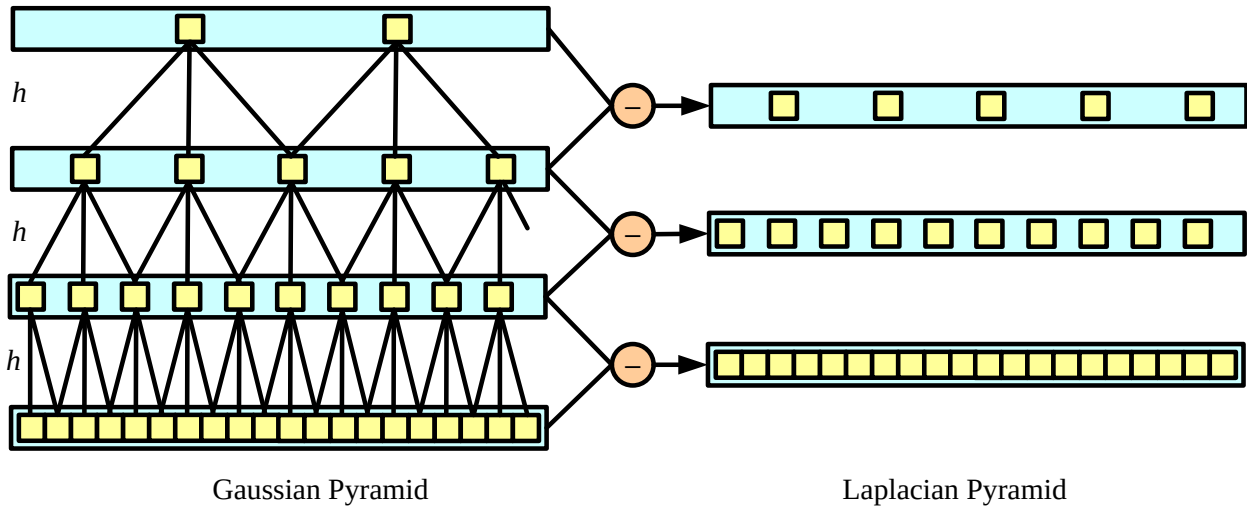


Fig. 3. Pyramid decomposition.

Now, instead of the output signal (g_1), it is enough to remember the pairs (g_2, d_1). The output signal can be accurately restored by the formula:

$$g_1 = d_1 + \tilde{g}_2 \quad (32)$$

The signal g_2 is twice as short as the original, and the signal d_1 , as a rule, consists almost entirely of very small quantities. Many of these quantities can be replaced with zeros without noticeable loss of accuracy, and the others can

be encoded with shorter bit lengths than the components of the output signal. Due to this, the total length of the record (g_2, d_1) will be significantly less than the length of the record of the output signal. This reduction will be even greater if several floors of the PL are calculated, and instead of the output signal, several floors of the LP and the last floor of the GP are stored.

The degree of information compression by this method depends on the choice of the filter h . During experiments with pyramidal representations, an observation was made: the “quality” of the filter is conveniently expressed in terms of an equivalent weight function.

It is not difficult to calculate the coefficients of the filters, the convolution of the signal with which immediately gives the second floor of the PG, the third floor, etc. It turns out that with appropriate normalization, the vectors of these coefficients converge to some limiting “form” – the graph of the function $\varphi(t)$, which must satisfy the functional equation:

$$\varphi\left(\frac{t}{2}\right) = \sqrt{2} \sum_k h_k \varphi(t - k). \quad (33)$$

Nonlinear multiscale decomposition. Figure 4 shows the order of operations performed when compressing by the proposed method.

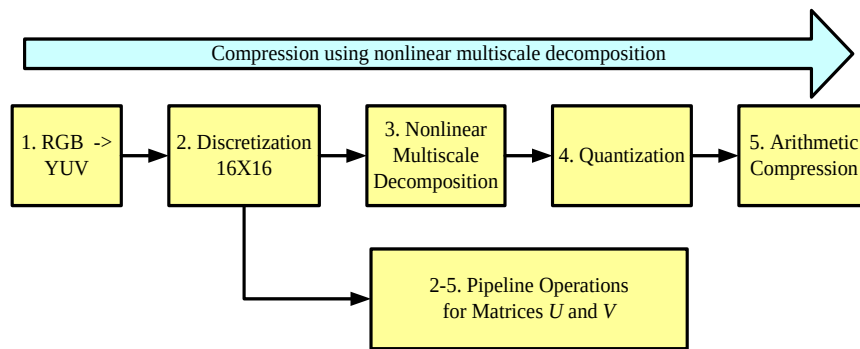


Fig. 4. Pipeline of operations in compression by the method based on nonlinear multiscale decomposition.

The proposed method can be presented as a step-by-step computational process:

Step 1. Color image conversion (RGB to YUV). In this case, the original RGB image is converted to YUV format, where the Y component is responsible for brightness, and U and V are for color components. Such conversion allows for more efficient further file compression since the human visual system is more sensitive to brightness than to color.

Step 2. Discretization (16×16). The converted image is divided into blocks of fixed size 16×16 pixels. Such a block structure facilitates local signal processing and simplifies the computational complexity of the following stages.

Step 3. Nonlinear multiscale decomposition. For each block, a nonlinear multiscale decomposition based on the application of fractional-rational approximation is carried out. Unlike existing transformations used in image processing, the proposed approach adapts to the local properties of the image, ensuring effective separation of structural components (contours, textures, and inhomogeneities). As a result of the decomposition, a set of coefficients of different scales with increased sparsity can be formed.

Step 4. Quantization. The obtained decomposition coefficients are quantized taking into account their significance. Less important coefficients are quantized more coarsely, which reduces the amount of data with minimal impact on visual quality.

Step 5. Arithmetic compression. This is the final stage, at which the quantized coefficients are compressed using arithmetic compression. This compression allows for effective elimination of statistical redundancy and forms the final compressed bit stream.

Steps 2–5 Parallel pipeline processing (for U and V components). The U and V components are processed in a similar way (discretization → decomposition → quantization → compression), but in the form of pipeline operations. This allows for increased processing efficiency without losing the quality of color information representation.

It should be noted that the nonlinear approximation based on fractional-rational functions in this case will be integrated into the multiscale decomposition at the processing level of each detailing component. After the image is decomposed into parts of different scales, a fractional-rational approximation will be applied to each of them, which will allow taking into account the local properties of the image. Iterative weighting is used to refine the approximation parameters by minimizing the recovery error due to a larger number of detailing coefficients. Thus, in general, the

nonlinear approximation is built into the process of multiscale analysis, increasing the efficiency of subsequent quantization and compression.

Two types of dependence are used in modeling. The first one is a quasilinear dependence, which is reduced to a linear dependence by replacing the smoothing variables. This method is very effective and it is often used in experimental processing, because a priori information about the physics of the process helps to find a good replacement of variables [58].

Another type of dependence on coefficients is fractional-linear, when the approximating function is rational:

$$\phi(x) = \frac{P_n(x)}{Q_m(x)} = \frac{\sum_{k=0}^n a_k x^k}{\sum_{q=0}^m b_q x^q} \quad (34)$$

Generalized polynomial relations are also frequently employed. Such an approximation captures the poles of the function $y(x)$ – they correspond to the zeros of the denominator of the required multiplicity. As a rule, it is possible to reproduce the asymptotic behavior $y(x)$ at $x \rightarrow \infty$ by appropriately choosing the quantity $n-m$; for example, if $y(\infty) = \text{const} \neq 0$, then we must take $n=m$. In this case n, m themselves can be taken large enough to have many approximation coefficients. We will use this method. But the square of the error $\left\| y - \frac{P_n}{Q_m} \right\|_{L_2}^2$ will no longer be a quadratic function of the coefficients, so finding the coefficients of a rational function is not easy.

By analogy with the mean square approximation by polynomials, we can hypothesize that the error $y(x) - \frac{P_n(x)}{Q_m(x)}$ has a number of zeros on the interval $[a, b]$, not less than the number of free coefficients. Then the problem is reduced to Lagrangian interpolation along these zeros x_p and the coefficients a_k, b_q are found from the system of linear equations:

$$y(x_p) \sum_{q=0}^m b_q x_p^q = \sum_{k=0}^n a_k x_p^k, \quad 0 \leq p \leq n+m; \quad b_0 = 1 \quad (35)$$

It is clear that the exact position of the zeros is not known; they are chosen arbitrarily, as a rule, evenly distributed on the segment $[a, b]$. This method is called the method of selected points. The approximation $\phi(x)$ obtained by this method will not be the best. In addition, the method of selected points is not better, as is any interpolation, if $y(x_p)$ has a noticeable error. The best approximation can be found by the iterated weight method. Note that the

$$\|Q_m(x)y(x) - P_n(x)\|_{L_2}^2 = \min \quad (36)$$

is easily solved: the expression on the left is a quadratic function of the coefficients a_k, b_q , and differentiation over them leads to a linear system for determining the coefficients. The new problem differs from the original one in essence in that a different weight $\rho(x)$ is used instead of the weight $\rho(x)Q_m^2(x)$, so its solution will not be the best approximation. Let us write the original problem in the new form:

$$\left\| y - \frac{P_n}{Q_m} \right\|_{L_2}^2 = \int_a^b \bar{\rho}(x) [Q_m(x)y(x) - P_n(x)]^2 dx = \min \quad (37)$$

$$\bar{\rho}(x) = \frac{\rho(x)}{Q_m^2(x)} \quad (38)$$

and we will solve it with a simple iterative process:

$$\bar{\rho}^{(s)}(x) = \rho(x) [Q_m^{(s-1)}(x)]^{-2} \quad (39)$$

$$\int_a^b \mathcal{P}^{(s)}(x) [Q_m^{(s)}(x)y(x) - P_n^{(s)}(x)]^2 dx = \min \quad (40)$$

for the zero approximation we can take $Q_m^{(0)}(x) \equiv 1$. At each iteration, the weight is known from the previous iteration, so the coefficients $a_k^{(s)}$, $b_q^{(s)}$ are easily found from the condition of the minimum of the quadratic form. Practice shows that the coefficients of the best approximation depend weakly on the choice of weight, so usually the iterations converge quickly.

One of the serious problems of machine graphics is that an adequate criterion for assessing image quality loss has not yet been found. It is lost constantly - during digitization, when translating into a limited color palette, translating into another color representation system for printing, and, which is especially important for us, during lossy compression. The measure that is currently used in practice is called the peak signal-to-noise ratio (PSNR).

$$d(x,y) = 10 \lg \frac{255^2 n^2}{\sum_{i=1, j=1}^{n,n} (x_{ij} - y_{ij})^2} \quad (41)$$

This measure is essentially similar to the standard deviation, but it is somewhat more convenient to use due to the logarithmic scale. It has the same disadvantages as the standard deviation.

Using this measure to assess the quality of compression, the following results were obtained (Figures 5, 6, 7, 8). Comparative analysis of the proposed method was carried out with the JPEG-2000 algorithm, which is an example of the application of modern wavelet-based approaches. This ensured the transparency and reproducibility of the results of experimental studies. The test images were selected from publicly available image databases. During the analysis, 1000 test images were utilized to estimate method performance.

Comparisons were performed on a set of high-resolution images (Figs. 5 – 8) with a color depth of 24 bits. To ensure the correctness of the comparison, the quantization parameters were set to achieve the same level of quality of the restored images, which was evaluated by the PSNR metric. The results shown in Figs. 5 – 8 demonstrate that for approximately the same PSNR values (within 35 – 48 dB) the proposed method provides a smaller file size after compression compared to JPEG-2000. In particular, for the image in Fig. 5, the size is reduced from 5310 Kbyte to 3800 Kbyte (reduction in file size is 28%), for Fig. 6 – from 3578 Kbyte to 3276 Kbyte (gain is 9.2%), for Fig. 7 – from 2971 Kbyte to 2700 Kbyte (gain is 10%), and Fig. 8 – from 5815 Kbyte to 5286 Kbyte (gain is 10%). This improvement corresponds to the presented images, but the method was also tested on 996 other test images.

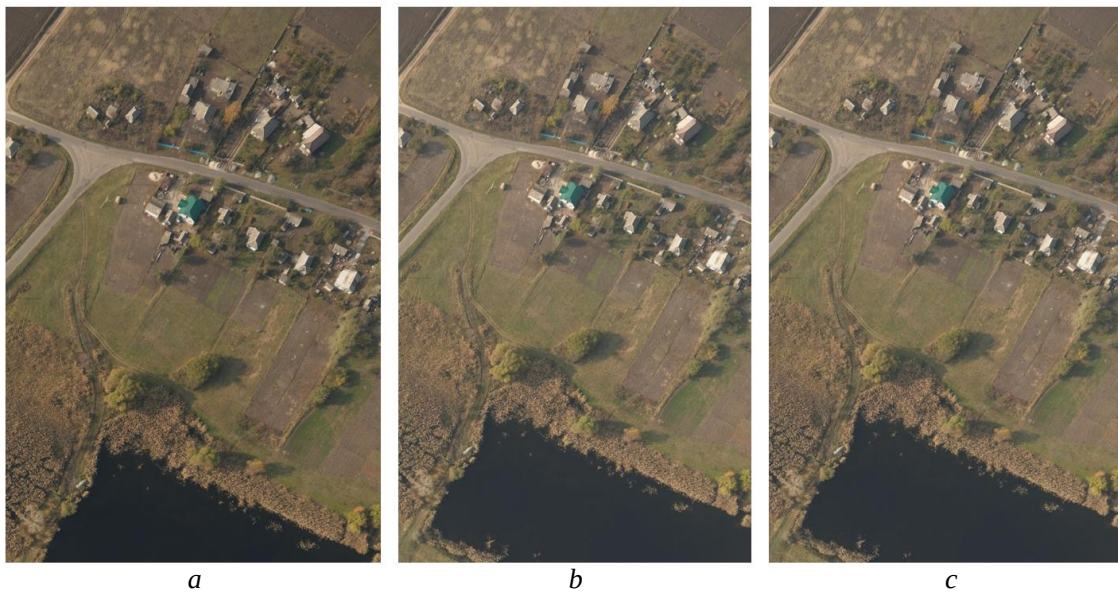


Fig. 5. Comparison of compressed images: *a* – original image (41 Mb), *b* – compression by the wavelet method (5.31 Mb), *c* – compression by the proposed method (3.8 Mb). The signal-to-noise ratio was: PSNR = 35.3 dB.



Fig. 6. Comparison of compressed images: *a* – original image (4288x2848x24b, 35779 Kb), *b* – compression by the wavelet method (JPEG-2000, 3578 Kbyte), *c* – compression by the proposed method (3276 Kbyte). The signal-to-noise ratio was: PSNR = 39 dB.



Fig. 7. Comparison of compressed images: *a* – original image (4948x3480x24b, 50447 Kbyte), *b* – compression by the wavelet method (JPEG-2000, 2971 Kbyte), *c* – compression by the proposed method (2700 Kbyte). The signal-to-noise ratio was: PSNR = 47.5 dB.

The obtained results for other images confirm that the use of nonlinear multiscale decomposition with fractional-rational approximation allows achieving a stable increase in the compression ratio (within 8 – 10% in average for 1000 test images) compared to wavelet methods without loss of visual quality.

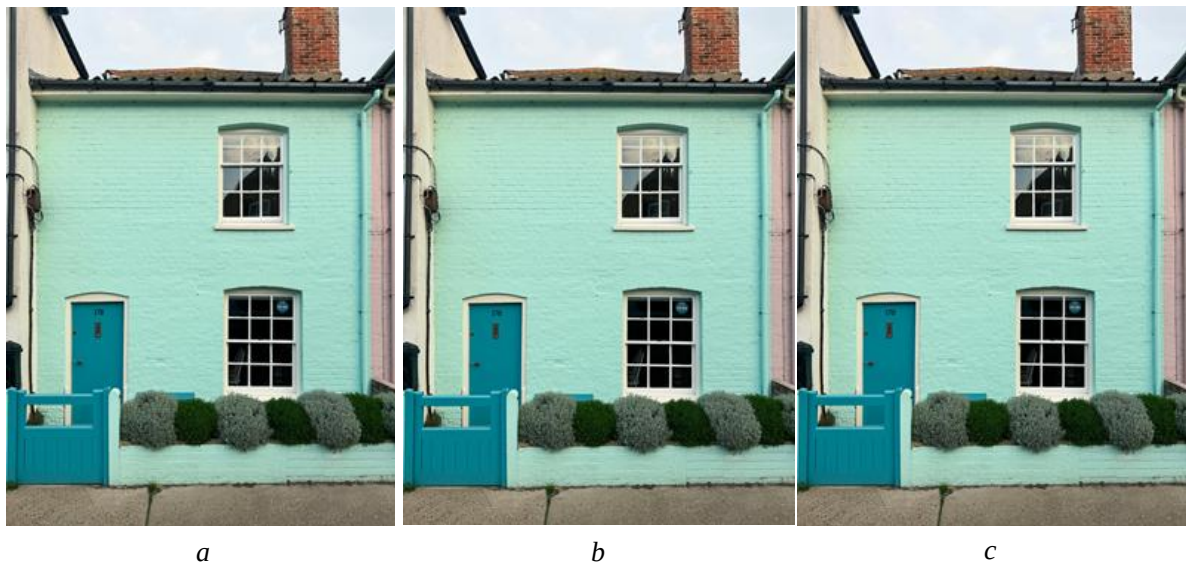


Fig. 8. Comparison of compressed images: *a* – original image (4284x5712x24b, 71691 Kbyte), *b* – compression by the wavelet method (JPEG-2000, 5815 Kbyte), *c* – compression by the proposed method (5286 Kbyte). The signal-to-noise ratio was: PSNR = 48 dB.

4. Conclusions

This article presents the synthesis and analysis of a novel image compression method based on nonlinear multiscale decomposition with fractional-rational approximation. The synthesis task was solved analytically. As a result, five steps of methodology were introduced, including image preprocessing, discretization, nonlinear multiscale decomposition, quantization, and arithmetic compression. The analysis task was solved using modeling.

The nonlinear multiscale decomposition approach is adaptive to local structures in the image and thus differs from existing methods based on linear wavelet transform with fixed basis functions. This feature allows for more effective representation of image components that are not accurately captured by standard wavelet basis functions. It should also be noted that, unlike classical approaches, where the decomposition is fixed and does not depend on the image content, the described method is based on a nonlinear decomposition mechanism, which provides better localization of informative components, uses adaptive discretization, which helps reduce the redundancy of the representation, and provides more efficient quantization and coding.

The proposed algorithm consists of five steps: image preprocessing, discretization, nonlinear multiscale decomposition, quantization, and arithmetic coding. The method was analytically formulated and evaluated through simulation on a dataset of 1000 test images.

Experimental results demonstrated that the proposed approach achieved an average compression ratio of 13.2 while maintaining a reconstruction quality of 41.5 dB. Under comparable conditions, the proposed method outperformed conventional wavelet-based compression techniques by approximately 8-10% in terms of the average compression ratio. Although the computational complexity of the proposed algorithm is higher than that of conventional wavelet-based methods, the obtained results indicate that it remains suitable for practical implementation.

Further research will focus on experimentally assessing the efficiency of the proposed method using other standard metrics, such as the Structural Similarity Index (SSIM), and by constructing rate-distortion curves. Such analysis will allow to clearly determine the degree of achieved compromise between the compression rate and the quality of restored images in comparison with modern approaches. Special attention will be paid to the study of the computational complexity of the algorithm, including the estimation of time costs and resource consumption for different decomposition and approximation parameters. Preliminary evaluation showed that the presented method has a longer compression duration, but decompression is fast. The authors plan to optimize the algorithm taking into account the features of parallel computing and hardware implementation for use in real-time image processing systems.

All the Declarations and Statements

Author Contributions Statement

Olena Kolhanova – Writing: Drafted the initial manuscript, contributed to the literature survey, and documented the technical background of the study.

Lidiia Tereshchenko – Data Curation and Software Implementation: Handled data acquisition, image processing, and implementing the research model.

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Iryna Morozova – Formal Analysis and Project Management: Performed in-depth analysis of experimental results and helped coordinate project milestones and deadlines.

Oleksandr Davydov – Conceptualization and Methodology: Proposed research ideas, and Results analysis.

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Maksym Zalyskyi – Writing: Final manuscript preparation, Review, and Editing: Reviewed and edited the manuscript, ensured clarity and coherence.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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Data Availability Statement

The data used in this study are publicly available and have been described in detail in the manuscript. No new data were generated or collected for this study.

Ethical Declarations

This study is based exclusively on publicly available datasets. All data used are fully anonymized and were collected in compliance with applicable ethical guidelines by the original data providers. Therefore, no additional ethical approval or informed consent was required for this study.

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Declaration of Generative AI in Scholarly Writing

The authors declare that no generative AI tools were used in the preparation of this manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

AI - Artificial Intelligence
 CT - Computed Tomography
 DFT - Discrete Fourier Transform
 GP - Gaussian Pyramid
 HEVC - High Efficiency Video Coding
 IIoT - Industrial Internet of Things
 JPEG - Joint Photographic Experts Group
 LP - Laplacian Pyramid
 MRI - Magnetic Resonance Imaging
 PSNR - Peak-To-Peak Signal-To-Noise Ratio
 QMF - Quadrature Mirror Filters
 UAS - Unmanned Aerial Systems

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