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# Comparative analysis of the quality of fractal image compression with JPEG and JPEG2000 standards

*This paper presents a comparative analysis of three image compression methods: JPEG, JPEG2000, and fractal compression (FIC). The theoretical foundations of each method are reviewed, including the discrete cosine transform (DCT) for JPEG, the discrete wavelet transform (DWT) for JPEG2000, and the iterated function system (IFS) for FIC. The performance of the algorithms is evaluated using a set of metrics: compression ratio (CR), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and the learned fragment image similarity metric (LPIPS). The analysis shows that JPEG2000 generally provides better quality at a given bitrate than JPEG, especially at high compression ratios, and offers additional features such as scalability, but this advantage is rather small. JPEG remains popular due to its simplicity and speed, but suffers from block artifacts. Fractal compression, despite its theoretical advantages, such as potential resolution independence, has significant drawbacks, including extremely slow encoding and often uncompetitive quality on general images. The application areas, reasons for limited implementation, and the current relevance of FIC are discussed. It is concluded that it is necessary to use various metrics for comprehensive quality assessment and that the choice of the optimal compression method depends on the specific requirements of the application.*

***Keywords***: *image, compression, lossy, lossless, fractal compression, LPIPS, PSNR, SSIM.*

**Introduction.** In the digital age, visual information plays an extremely important role in many areas, from everyday communication and entertainment to highly specialized industries such as medicine, remote sensing of the Earth, and scientific research. The rapid growth of the volume of generated and processed digital images in various fields, including multimedia and consumer technology, places an urgent need for efficient methods of their storage and transmission. Despite the constant improvement of hardware, the volume of uncompressed images often exceeds the available memory resources and bandwidth of communication channels, making image compression not just a useful option, but an urgent necessity. The basis for solving this problem are image compression algorithms, the goal of which is to reduce data redundancy while preserving visually meaningful information. The effectiveness of any compression algorithm is determined by the balance between the achieved compression ratio (Compression Ratio, CR) and the quality of the restored image.

There are many approaches to image compression, each with its own characteristics and applications. One of the most widely used and versatile standards is JPEG, which has gained widespread acceptance for its effectiveness for photographic images, especially in the web and consumer electronics. Its successor, JPEG 2000, offered significant improvements, including better quality at high compression ratios, scalability, and support for lossless compression, making it valuable in critical areas such as medical imaging, high-quality image archiving, and professional graphics processing. In addition to transformation-based standards, alternative methods have been explored, including fractal compression, which uses the principles of image self-similarity and can be effective for certain types of visual data, although it is more computationally intensive [1]. The choice of the optimal compression method depends on the specific quality, speed, and purpose of the compressed image.

**Analysis of recent research and problem statement.** Fractal concepts find application even in the field of lossless compression (lossless compression), especially for specific data types. The CompaCT algorithm is designed for efficient lossless compression of high bit depth medical images (e.g. 12-bit monochrome DICOM images such as CT scans). CompaCT is claimed to demonstrate significantly better compression ratios than standard lossless compression methods used in medicine such as JPEG2000-Lossless (approximately 37% more space efficient), while guaranteeing full recovery of the original data [2]. CompaCT's success in lossless compression of medical images using fractal scanning challenges the historical association of fractals with primarily lossy compression. This highlights the usefulness of space - filling fractal curves), to optimize the data order before the next standard encoding steps (delta, entropy). The significant improvements compared to standard lossless methods demonstrate the practical value of such fractal preprocessing in the lossless compression pipeline. This broadens the scope of fractal techniques in compression, showing their relevance even where perfect recovery is required [2].

Fractal ideas also penetrate the field of generative modeling. The concept of Fractal Generative Models (Fractal Generative Models), where a generative model is built by recursively calling models of the same type within itself. For example, an autoregressive model can consist of modules that are themselves autoregressive models. This recursive strategy leads to complex architectures with self-similarity at different levels of modules, similar to fractal structures in nature or biological neural networks. This approach is potentially suitable for modeling non-sequential data with internal multi-scale structure. Its effectiveness has been demonstrated on the complex problem of pixel-by-pixel image generation, where it showed high generation quality and accuracy of likelihood estimation [3, 4].

There are several approaches to compression, among which JPEG and JPEG2000 are the most common, while fractal compression (FIC) offers an alternative approach based on image self-similarity [1]. However, comparing the performance of these methods is complicated by their different underlying principles and the types of artifacts they introduce. Traditional quality metrics, such as PSNR, often correlate poorly with human subjective perception of quality. Therefore, the problem arises of objectively and comprehensively assessing the quality and performance of fractal compression compared to JPEG and JPEG2000. This problem requires the use of a set of metrics that include both objective indicators (CR, PSNR) and metrics that better reflect human perception (SSIM, LPIPS) to analyze the trade-offs between compression rate, image quality, and computational complexity, as well as to determine the practical feasibility and potential niche applications of fractal compression in a modern context.

**The purpose and tasks of the study.** The main goal of this study is to conduct a comprehensive comparative analysis of the effectiveness of fractal image compression (FIC) relative to the widely used JPEG and JPEG2000 standards, using a set of objective and perceptual quality metrics. To present in detail the theoretical foundations and algorithmic steps of JPEG (DCP-based), JPEG2000 (DVP-based), and fractal compression (SIF-based) compression methods. To analyze the types of artifacts characteristic of each method. To analyze the strengths and weaknesses of each method, including the computational complexity of encoding and decoding. To separately consider potential areas of application and reasons for the limited implementation of fractal compression.

**Materials and methods of research.** Among the main compression methods that have gained popularity and are widely used are the J PEG and J PEG2000 methods. The fractal compression method is much less common and no less interesting. Let's consider them in more detail.

*JPEG compression standard***.** JPEG (Joint Image File Format) Photographic Experts Group) is a lossy compression standard based on dividing an image into 8x8 pixel blocks and applying a Discrete Cosine Transform (DCT) to each block. The purpose of DCT is to correlate pixel values within a block,

concentrating most of the signal energy in the low-frequency coefficients.
The JPEG compression process includes the following steps:

1. Color space conversion: Typically, an image is converted from RGB to YCbCr. This allows for chroma thinning to be applied. subsampling), reducing the resolution of the Cb and Cr components, since human vision is less sensitive to color details than to brightness.
2. Block division: The image is divided into non-overlapping blocks of 8x8 pixels.
3. Discrete Cosine Transform (DCT): DCT is applied to each 8x8 block, converting pixel values from the spatial domain to the frequency domain. The first coefficient (DC) represents the average brightness of the block, the rest (AC) represent high-frequency details.
4. Quantization: This is the key step where data loss occurs. Each DCT coefficient is divided by the corresponding value from the quantization table (larger values for higher frequencies, resulting in greater information loss) and rounded to the nearest integer. This process is controlled by the quality parameter (quality factor).
5. Zigzag scanning: The quantized coefficients are reordered from low frequencies to high frequencies in a zigzag pattern. This groups zero coefficients together, which increases the efficiency of the next stage.
6. Entropy coding: A lossless compression method (usually Huffman coding, sometimes arithmetic coding) is applied to the reordered coefficients to efficiently represent the quantized data stream.

Advantages: Easy to implement, widespread, fast decoding.

Disadvantages: At low bitrates (high compression ratios), characteristic "block artifacts" appear due to independent processing of 8x8 blocks. The standard does not provide scalability or robust error tolerance compared to JPEG2000 [5].

JPEG's reliance on fixed 8x8 blocks and DCT is both its strength (simplicity) and its weakness. The characteristic block artifacts that appear at the boundaries of these blocks when quantized heavily are its visual signature. This predictability makes it a useful baseline for comparison, but also highlights its limitations, especially compared to methods that use other approaches such as JPEG2000 (based on wavelets, which produces smoother artifacts) or FIC (with potentially other types of artifacts related to the self-similarity mapping). Understanding this type of artifact is key to interpreting comparative metric scores (e.g., SSIM may penalize blocking more heavily than PSNR).

*JPEG2000 compression standard*. JPEG2000 uses a Discrete Wavelet Transform (DWT) applied to the entire image or large tiles, providing a multi-level representation of the signal. This overcomes the blocky artifacts characteristic of JPEG and provides better concentration of signal energy.
The JPEG2000 algorithm includes the following steps:

1. Color space conversion: Various conversions are supported, including reversible (for lossless compression) and irreversible (for lossy compression).

2. Tiling (optional): The image can be divided into rectangular tiles that are processed independently. This improves memory efficiency for large images.

3. Discrete Wavelet Transform (DWT): Applied to tiles (or the entire image). DWT decomposes the image into different frequency subbands at multiple resolution levels (e.g. using the Cohen-Daubechy-Favo 9/7 wavelet for lossy compression or the LeGall 5/3 wavelet for lossless compression).

4. Quantization: Scalar quantization is applied to the wavelet coefficients in each subband. This allows for precise control of the bitrate.

5. Entropy Coding (EBCOT): Embedded Block Coding with Optimized Truncation (Embedded Block Coding with Optimized Truncation). Coefficients within subbands are grouped into code blocks that are coded bit-by-bit independently. This creates an embedded bitstream where layers can be truncated to achieve the desired bitrate or resolution. This multi-layer coding provides scalability.

Advantages: Higher compression efficiency, usually achieves better quality than JPEG at the same bitrate, especially at low bitrates. Lossy and lossless compression possible, supports both modes within a single standard. Scalability, progressive transmission by quality (SNR scalability) or resolution (resolution) scalability). Regions of interest (ROI) coding is also implemented, which allows coding certain areas of the image with higher accuracy. Increased error tolerance, better handling of errors in the bitstream compared to JPEG [1, 6].

Disadvantages: At low bitrates the characteristic "blocking artifacts" still appear.

JPEG2000 limitations and advantages: higher computational complexity of encoding and decoding compared to JPEG, less widespread native support in web browsers and basic image viewers. A key advantage of JPEG2000, resulting from the use of DVP and EBCOT, is its intrinsic scalability. A single compressed file can serve different purposes (thumbnail, screen resolution, full quality) without the need for re-encoding. This is in sharp contrast to JPEG (where separate files are required for different qualities/ resolutions) and FIC (where decoding is iterative and resolution independence is theoretical, but practical scaling may require repeated decoding). EBCOT organizes the bitstream into quality layers, allowing the decoder to stop reading the stream at any point and restore the image at the appropriate quality or resolution. This property fundamentally changes the way compressed data is used compared to JPEG, where the entire file must be decoded to obtain a complete image. This makes JPEG2000 particularly suitable for applications such as medical image archives or content delivery networks (CDNs) [7, 8].

*Fractal Image Compression (FIC).* Fractal compression is based on the mathematics of Systems of Iterated Functions (SIF) and the Collage Theorem (Barnsley). The basic idea is that the redundancy of an image can be described by finding parts of the image (domain blocks, DB) that, after simple geometric and contrast transformations (affine mappings), can approximate other parts of the image (rank blocks, RB). The image is represented by a set of these transformations, rather than by pixel values [9].

Coding process.

1. Image partitioning: The image is partitioned into non-overlapping 'rank blocks' (RBs). A separate collection of potentially larger, possibly overlapping 'domain blocks' (DBs) is created.
2. Self-similarity search: For each rank block, the encoder searches among the domain blocks for the best match after applying an affine transformation (typically involving scaling, rotation/reflection, brightness shift, contrast scaling). This search is the computational bottleneck of the algorithm.
3. Transformation parameters: The parameters of the best affine transformation (spatial compression, isometry, brightness/contrast settings) and the location of the best domain block are stored for each rank block. Quantization is applied to these parameters.

Decoding process.

1. It starts with an arbitrary initial image.
2. iteratively applied to the current image, mapping the contents of the domain blocks (transformed) to the corresponding positions of the rank blocks.
3. Due to the compressibility property of transformations, this iterative process converges to a stable attractor – an image that is a restored approximation of the original.

Key features:

- Potential for high compression ratios, especially for images with significant self-similarity (e.g. textures).
- Resolution independence (theoretical), since the image is represented by transforms, decoding can potentially occur at a higher resolution than the original, generating plausible details (though not necessarily accurate high-frequency information).
- Extremely slow coding due to extensive search process, there are various optimization methods (e.g. block classification), but this remains the main drawback.
- Typically faster than encoding, but the iterative nature may be slower than basic JPEG decoding.
- Artifacts may differ from JPEG/JPEG2000, with possible loss of fine texture or "fractal-like" artifacts if the conversions are inaccurate.

The fundamental asymmetry between slow encoding and faster decoding in FIC is a direct consequence of its reliance on self-similarity search. Encoding requires exhaustive search, while decoding is a deterministic iterative application of the found transforms. This significant time difference (encoding is slow, decoding is faster) has profoundly affected the practical implementation of FIC. Scenarios that require fast encoding (e.g., digital cameras, real-time video conferencing) are poorly suited to FIC. It may be more viable for archival scenarios (encode once, decode many times), but even there it competes with standards that offer better overall performance or functionality [10].

Although resolution independence is often cited as a key advantage of FIC, its practical value is debatable. Higher-resolution decoding essentially interpolates data based on learned self-similarities. This can generate visually plausible details, especially for textures, but does not recover high-frequency information lost during encoding. Modern super-resolution methods (often based on deep learning) may offer more efficient ways to increase image resolution. The benefits of this approach should be assessed in terms of achievable quality and compared to alternative upscaling methods [11].

*Image quality assessment metrics.* Evaluating the performance of compression algorithms with different underlying mechanisms (DCP, DVP, SIF) requires metrics that capture different aspects of reproduction accuracy and perceptual image quality.

Compression ratio (CR) - the ratio of the size of the original uncompressed image to the size of the compressed file. Measures the primary goal of compression - reducing the amount of data. Higher CR means stronger compression. Does not provide information about quality.

Peak signal-to-noise ratio (PSNR) is based on the mean square error (MSE) between the original (I) and reconstructed (K) images of size M×N.

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[ I(i,j) - K(i,j) \right]^2 \tag{1}$$

$$PSNR = 10 \cdot \log_{10} \left( \frac{MAX_I^2}{MSE} \right) \tag{2}$$

where $MAX_I$ is the maximum possible pixel value (for example, 255 for an 8-bit gradation image).

Historically, the standard metric, which is easy to compute, measures per-pixel accuracy. A higher PSNR typically indicates lower per-pixel error. But the metric has a poor correlation with human perception of quality; it penalizes all errors equally, regardless of image content or structure. It can be misleading when comparing different types of artifacts (e.g., blurring versus blocking) [12].

The Structural Similarity Index (SSIM) measures perceived similarity based on structural information by comparing local patterns pixel intensities, normalized by brightness and contrast. Computed locally and averaged.

$$SSIM(x,y) = \left[ l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma} \right] \tag{3}$$

Typically α=β=γ=1. Component l compares brightness, c compares contrast, s compares structure (using covariance /correlation).

Designed to better match human visual perception than PSNR, focusing on structural changes. Values range from -1 to 1 (or 0 to 1), where 1 represents perfect similarity. The metric has some limitations: it is still based on relatively simple statistical comparisons of image fragments; it may not accurately capture complex texture distortions or suprathreshold artifacts [12, 13].

Trained image fragment similarity metric (LPIPS). A "perceptual distance" metric that uses deep convolutional neural networks (CNNs, e.g., VGG, AlexNet) pre-trained on large image datasets (such as ImageNet). It computes the distance between activations at intermediate layers of the network for fragments of the reference and distorted images. Lower LPIPS values indicate greater perceptual similarity. It uses features learned by deep networks that are known to correlate well with human object and texture recognition, thus aiming for better agreement with human perceptual similarity/quality estimates than PSNR or SSIM. Particularly useful for evaluating generative models or distortions that are poorly captured by traditional metrics. Limitations of the metric - requires pre-trained networks, is computationally more expensive than PSNR/SSIM, and performance may depend on the specific network architecture and training data. Its interpretation as a universal quality metric is still evolving.

The selected metrics form a hierarchy of complexity and perceptual relevance. CR measures efficiency. PSNR measures per-pixel error. SSIM measures structural error. LPIPS measures perceptual distance based on deep features. Using them together provides a more holistic view. For example, FIC may achieve high CR but lower PSNR/SSIM than JPEG2000 at the same CR, but LPIPS may evaluate it differently depending on the nature of the artifacts, potentially revealing cases where its distortions are perceptually less unpleasant despite per-pixel /structural differences. Comparing algorithms such as JPEG (blocking), JPEG2000 (blurring), and FIC (potential texture/self-similarity artifacts) requires such a multifaceted approach, as each metric may evaluate different types of artifacts differently.

The progression from PSNR to SSIM and then to LPIPS reflects the ongoing research effort in computational modeling of human visual perception. The limitations of PSNR motivated the development of SSIM, and the quest for even better perceptual correlation, especially for complex distortions, led to the emergence of learning-based metrics such as LPIPS. This evolution emphasizes that "image quality" is not a fixed concept, and our tools for measuring it are constantly improving. This means that evaluating compression algorithms requires the use of metrics that reflect current understanding of perceptual quality, making LPIPS particularly relevant alongside established standards [14, 15, 16].

*Quality assessment of compression methods on samples.* For compression comparison, samples of 512x512 pixels were taken and compressed with the same compression ratio. The first sample for the study is a photograph of brickwork (Fig. 1). The applied compression ratio (CR) for all algorithms for this image is 6.5. Fig. 2.1, 2.2., in an enlarged form, show the distortions that occur when compressing JPEG, JPEG 2000, FIC, respectively.

The figures clearly show minimal distortion when compressing FIC, preserving boundaries and colors. The JPEG sample clearly shows 8 x 8 areas, and JPEG 2000 compression shows strong blurring. But brickwork is an example of an image with a large number of similar fragments that can be used in compression due to affine transformation. Table 1 shows comparative metrics. PSNR is indicated in dB (the higher, the better), the pixel-by-pixel restoration accuracy of all methods is very close and is within 2.4%, although the visual difference is very noticeable. This indicates the weakness of this metric for evaluating compression algorithms. The structural similarity index (SSIM, the closer to 1, the better) is a perceptual metric that evaluates the structural similarity between the original and restored images, taking into account brightness, contrast and structure, but it also gives a difference of 2.1%. Moreover, the SSIM metric gives an advantage to the SSIM algorithm even with an obvious blur factor. LPIPS is a similarity metric of image fragments, designed for better correlation with the human perception of image similarity. It is it that gives an advantage to the FIC algorithm with a gap of 58% and 25% over JPEG and JPEG2000, respectively. Judging by the examples given, it is this metric that most accurately shows the similarity of images from a human perspective.

*Table 1.* **Comparison of JPEG, JPEG2000 and Fractal compression (FIC) of Figure 1**

| Compression ratio (CR) | Algorithm | PSNR (dB) | SSIM | LPIPS |
|---|---|---|---|---|
| 6.5:1 | JPEG | 28.7013 | 0.7704 | 0.1352 |
| | JPEG2000 | 29.1834 | 0.7915 | 0.1067 |
| | FIC | 28.4859 | 0.7767 | 0.0854 |

The second example for comparing compression algorithms is a lung X-ray, which is widely used in medicine (Fig. 3).

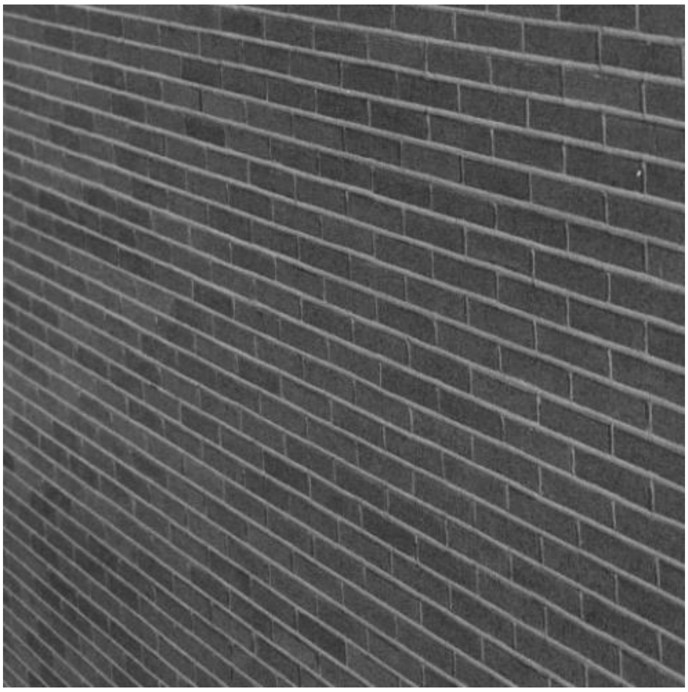

*Fig. 1.* **Brickwork**

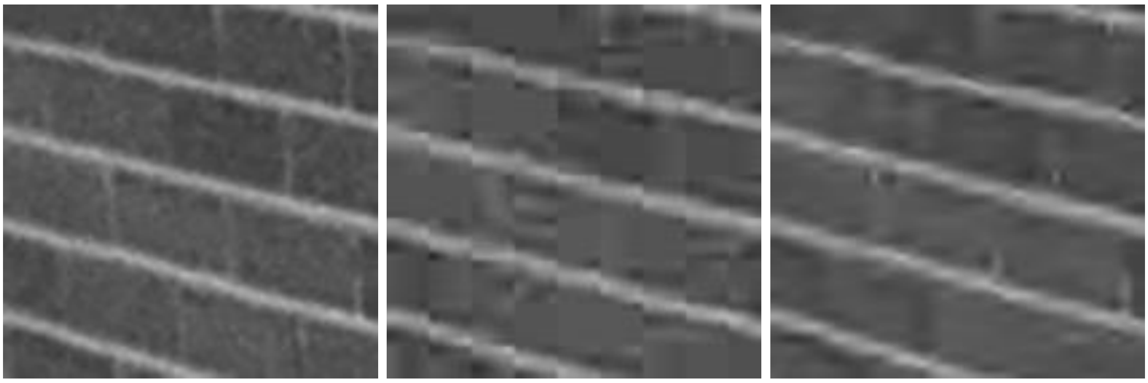

*Fig. 2.1.* **Brickwork. Original image, compressed JPEG, compressed JPEG 2000**

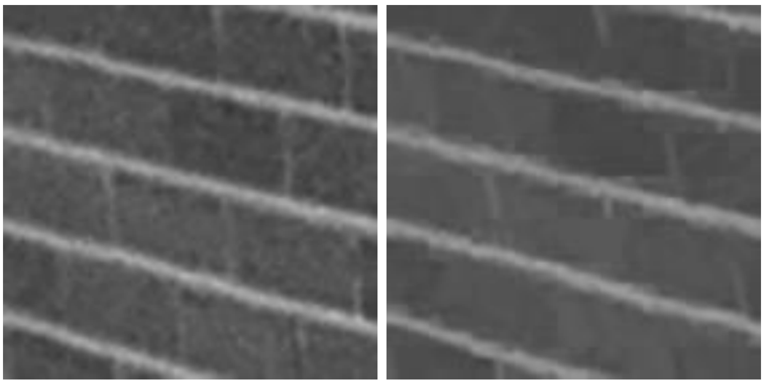

*Fig. 2.2.* **Brickwork. Original image, image compressed FIC**

*Fig. 3.* **Lung X-ray**

The applied compression ratio (CR) for all algorithms for this image is 5.2. Fig. 3.1, 3.2., in an enlarged form, show the distortions that occur when compressing JPEG, JPEG 2000, FIC.

The figures clearly show minimal distortion when compressing JPEG and JPEG 2000, the edges and colors are preserved. The FIC sample clearly shows 8 x 8 areas. X-ray is an example of an image with clear boundaries, a large number of areas filled with a gradient. Table 2 shows comparative metrics. Although the image reproduction quality in all algorithms is very high, the PSNR of FIC is worse than JPEG and JPEG2000 by 15% and 17%, SSIM is worse by 1.7%. LPIPS is almost 6 times worse, but this is not very noticeable from a human point of view because the level of 0.0383 is very close to 0. Nevertheless, for X-rays, FIC performed worse than the JPEG family. This is explained by the small number of similar fractals, although it seems that the edges are almost the same, not all fragments can be converted to similar ones by affine methods.

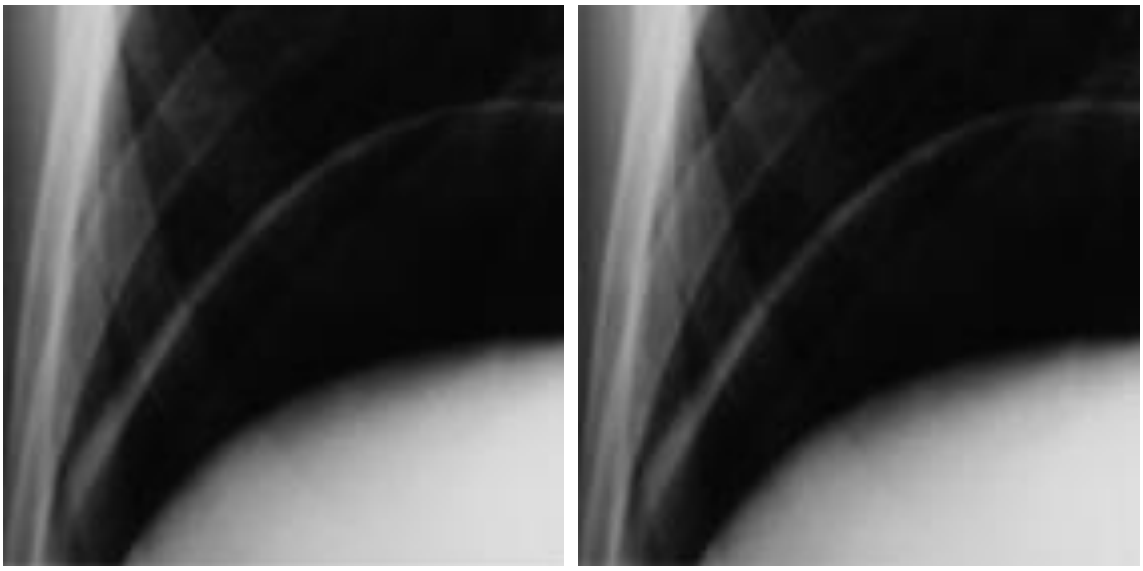

*Fig. 3.1.* **Lung X-ray. Original image, compressed JPEG**

*Fig. 3.2.* **Lung X-ray. Image compressed JPEG 2000, compressed FIC**

*Table 2.* **Comparison of JPEG, JPEG2000 and Fractal compression Compression (FIC) of Figure 3**

| Compression ratio (CR) | Algorithm | PSNR (dB) | SSIM | LPIPS |
|---|---|---|---|---|
| 5.2:1 | JPEG | 46.3723 | 0.9905 | 0.0056 |
| | JPEG2000 | 47.2023 | 0.9900 | 0.0066 |
| | FIC | 40.2540 | 0.9730 | 0.0383 |

The third example for comparing compression algorithms is a satellite image (Fig. 4).

*Fig. 4.* **Satellite image**

The applied compression ratio (CR) for all algorithms for this image is 5.2. Fig. 4.1, 4.2., in an enlarged form, show the distortions that occur when compressing JPEG, JPEG 2000, FIC.

*Fig. 4.1.* **Satellite image. Original image, JPEG compressed**

The figures clearly show the worse quality of the FIC compression algorithm, which can be explained by the rather large size of the rank block of 8 x 8 pixels, which does not allow reproducing small details. But when the block is reduced to 4 x 4 pixels, the number of blocks and, accordingly, the size of the compressed file increases 4 times. It is precisely for the purpose of comparison that the CR algorithms were brought to the same level. Comparative metrics are shown in Table 3.

*Fig. 4.2.* **Satellite image. Image compressed JPEG 2000, compressed FIC**

Small details revealed the weakness of the FIC algorithm compared to JPEG and JPEG2000 at the same CR. The main LPIPS metric is more than 2 times worse in FIC compared to JPEG, this is very noticeable on small details, although the overall level of 0.1653 is high.

*Table 3.* **Comparison of JPEG, JPEG2000 and Fractal compression Compression (FIC) of Figure 4**

| Compression ratio (CR) | Algorithm | PSNR (dB) | SSIM | LPIPS |
|---|---|---|---|---|
| 5.2:1 | JPEG | 31.0731 | 0.8334 | 0.0771 |
| | JPEG2000 | 31.6100 | 0.8364 | 0.1042 |
| | FIC | 27.2289 | 0.7250 | 0.1653 |

The analysis shows an inevitable trade-off between compression efficiency (CR), objective quality (PSNR), structural quality (SSIM), perceptual quality (LPIPS), and computational cost (encoding/decoding time). JPEG2000 generally offers the best balance of quality and compression for natural images, but at the expense of higher complexity compared to JPEG. JPEG remains popular due to its simplicity and speed, despite quality limitations at high CRs [17, 18]. FIC, despite its theoretical advantages, suffers from extremely slow encoding and often uncompetitive quality on general images.

Although JPEG2000 generally dominates the "bitrate-to-distortion" ratio for natural images, FIC's unique mechanism exploiting self-similarity suggests that it could have a niche for images rich in repeating patterns or textures. Theoretically, for such images, the self-similarity model could be more efficient than the frequency model (DCP/DVP), potentially resulting in better compression or quality for these specific images. However, empirical data often shows it to lag behind. This suggests that FIC's strengths, if they exist, are likely limited to specific classes of images, making it less suitable as a universal standard.

Including LPIPS can potentially change the perceived rating, especially between FIC and JPEG. If FIC produces artifacts that look "unnatural" but do not destroy the structure as much as blocking (less impacting SSIM) or pixel values (less impacting PSNR), LPIPS may penalize it heavily. Conversely, if its artifacts are perceptually smoother or less obtrusive than strong blocking, LPIPS may rate it higher than a relatively low-quality JPEG than PSNR/SSIM. This highlights the importance of using metrics that are consistent with the intended application (e.g., human viewing vs. machine analysis).

The choice of the "best" method depends heavily on the specific requirements of the application: the required quality, the constraints on encoding speed, the need for features such as scalability, etc. Today, FIC is mostly considered a niche technique with historical significance. Although research into optimizing FIC algorithms or exploring hybrid approaches is ongoing, it is not a mainstream compression method [19]. Its basic ideas (the use of self-similarity) may find application in other areas such as analysis or texture generation, or potentially inspire aspects of future compression schemes [20]. Even if FIC has failed as a mainstream compression standard, the basic concept of exploiting structural self-similarity in data is powerful. This idea finds resonance in other areas of computer vision and graphics, such as texture synthesis, image augmentation (inpainting), and potentially in the development of generative models. FIC research, even if commercially unsuccessful, contributed to a broader understanding of image statistics and redundancy. Texture synthesis techniques explicitly search for and reproduce similar patterns. Image redrawing algorithms can fill in missing areas by copying and transforming similar existing regions. Generative adversarial networks (GANs) learn complex data distributions, which implicitly involves capturing repeating structures. Thus, the intellectual contribution of FIC goes beyond its direct application in compression, influencing related fields dealing with the modeling and manipulation of image structure.

Although FIC represents an intellectually exciting approach to CIF-based image compression, its practical limitations, including coding complexity and inconsistent performance advantages over standardized methods such as JPEG2000, have prevented its widespread adoption. JPEG2000 remains a technically superior standard compared to JPEG, although its adoption has been constrained by factors beyond pure performance. The history of these compression standards illustrates the phenomenon of path dependence (dependency): Early choices (like JPEG standardization) create ecosystems and user bases that make it difficult to completely supplant technically more advanced but later or more complex technologies (like JPEG2000 or FIC), even if they offer advantages.

**Conclusions**. The study compared the effectiveness of three image compression algorithms – JPEG, JPEG2000, and fractal compression (FIC) – on different types of samples (texture, medical image, satellite image) at the same compression ratios.

The analysis showed that the effectiveness of each method significantly depends on the characteristics of the image itself. Fractal compression demonstrated the best visual results and LPIPS perceptual metric performance on an image with a high degree of self-similarity (brickwork), significantly outperforming JPEG and JPEG2000 (by 58% and 25%, respectively) in terms of human perception of quality, despite the close values of the traditional PSNR and SSIM metrics. This emphasizes the limitations of PSNR and SSIM for a complete assessment of visual quality and the superiority of LPIPS in reflecting human perception. However, on images with fewer repeating fractal elements, clear boundaries (lung X-ray) or a large number of fine details (satellite image), FIC significantly lost ground to the JPEG family algorithms, LPIPS is 60% lower in FIC compared to JPEG2000. Visually, the FIC method also created more distortions - the appearance of blocky artifacts, loss of detail. For such images, JPEG and JPEG2000 provided significantly higher reproduction quality at a given compression ratio.

The study confirms that the choice of the optimal compression method is a trade-off between compression ratio, quality (objective, structural, and perceptual), and computational complexity, especially considering the extremely high encoding time for FIC. Although JPEG2000 often offers a better balance of quality and compression compared to JPEG, the latter remains popular due to its simplicity and speed.

Fractal compression, despite its theoretical potential for certain classes of images, remains niche due to practical drawbacks (slow encoding, uncompetitive quality on general images). The choice of compression algorithm remains application-specific, requiring a balance between quality, compression ratio, functionality, and computational resources.

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## Порівняльний аналіз якості фрактального стиснення зображень із стандартами JPEG та JPEG2000

*У цій статті представлено порівняльний аналіз трьох методів стиснення зображень: JPEG, JPEG2000 та фрактального стиснення (FIC). Розглянуто теоретичні основи кожного методу, включаючи дискретне косинусне перетворення (ДКП) для JPEG, дискретне вейвлет-перетворення (ДВП) для JPEG2000 та системи ітерованих функцій (СІФ) для FIC. Ефективність алгоритмів оцінюється за допомогою набору метрик: коефіцієнт стиснення (CR), пікове відношення сигналу до шуму (PSNR), індекс структурної подібності (SSIM) та навчена метрика подібності фрагментів зображення (LPIPS). Аналіз показує, що JPEG2000 зазвичай забезпечує кращу якість при заданому бітрейті порівняно з JPEG, особливо при високих коефіцієнтах стиснення, та пропонує додаткові функції, такі як масштабованість, але ця перевага досить невелика. JPEG залишається популярним завдяки простоті та швидкості, але страждає від блокових артефактів. Фрактальне стиснення, незважаючи на теоретичні переваги, такі як потенційна незалежність від роздільної здатності, має суттєві недоліки, зокрема надзвичайно повільне кодування та часто неконкурентоспроможну якість на загальних зображеннях. Обговорюються сфери застосування, причини обмеженого впровадження та сучасна актуальність FIC. Робиться висновок про необхідність використання різноманітних метрик для комплексної оцінки якості та про те, що вибір оптимального методу стиснення залежить від конкретних вимог програми.*

***Ключові слова**: зображення, стиснення, з втратами, без втрат, фрактальне стиснення, LPIPS, PSNR, SSIM.*