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Analysis of video image compression methods with partial information loss for medical information and measurement systems

An important part of information and measurement systems and databases in medical applications is patient information recorded as video images. These images may be formed in the visible light range or may be recordings of results obtained in other radiation ranges. All of this leads to an increase in the volume of medical data. The transition from paper to electronic records has also significantly increased the amount of data that must be stored and processed. Efficient storage of such information is impossible without reducing its volume based on compression procedures, including those that involve some loss of information. At the same time, it is necessary to ensure distortions are insignificant for visual perception of the images and cause only minor errors in the results of measuring informative parameters of the video signal. This article examines methods of compressing video images with partial information loss for medical information and measurement systems based on partial exclusion of color information, transformation-based encoding, and the JPEG compression method. Their advantages and disadvantages are analyzed.

Keywords: *information and measurement system; medical diagnostic images; video images; methods of compression with partial information loss; JPEG compression.*

Relevance of the Topic. In the modern world, the volume of medical data is growing rapidly. The introduction of electronic medical records (EMRs), medical imaging, and other digital medical resources creates vast amounts of data that require efficient storage and processing. In this regard, methods and algorithms for encoding and compressing information in medical data become critically important for ensuring quick access, storage, and transmission of information.

Like many other countries, Ukraine faces challenges in the healthcare sector related to the transition to electronic medical records and the digitization of medical services [1]. The implementation of modern methods of encoding and compressing information can significantly improve the quality of healthcare services in the country.

Increase in Medical Data Volume. The shift from paper to electronic records has significantly increased the volume of data that needs to be stored and processed. For example, EMRs ensure the preservation of all aspects of patient histories, including diagnoses, treatments, laboratory results, and other clinical information.

Use of Medical Imaging. Various imaging methods, such as magnetic resonance imaging (MRI), computed tomography (CT), and ultrasound (US), create vast amounts of high-quality images. These images require efficient compression without quality loss to ensure quick loading and analysis, as a single MRI session can generate up to 1,000 images that need to be stored.

Data from Wearable Devices. The growing popularity of wearable devices for health monitoring, such as smartwatches and fitness trackers, adds an additional stream of data. These devices collect information about heart rate, blood oxygen levels, physical activity, and other parameters, which require reliable methods of encoding and compression for efficient storage and analysis.

Storage Limitations. Traditional storage methods often struggle to cope with the growing volumes of data, necessitating new methods of efficient compression. Storage optimization is important to reduce infrastructure costs and increase data availability. This is particularly crucial for hospitals and medical centers with limited storage resources.

Fast Data Transmission. The quick and secure transmission of medical data between different medical institutions is critical for ensuring continuity of care. Compression algorithms help reduce the volume of transmitted data, contributing to faster information exchange and improving the efficiency of medical workers. For example, in telemedicine, the rapid transmission of images and records is essential for providing timely medical consultations.

Ensuring Confidentiality and Security. Medical data are highly sensitive, and their compression and transmission must take into account issues of confidentiality and security. The use of encoding methods that ensure data protection during transmission and storage is an important aspect of modern medicine. According to a report by HIPAA Journal, more than 700 incidents of medical data breaches occurred in 2023, underscoring the importance of security during the compression and transmission of data [2].

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Integration with Medical Standards. The use of specific medical standards, such as HL7 and DICOM, for efficient encoding and integration of medical data is necessary to ensure compatibility between different medical systems and devices. This allows for data from different sources to be combined for comprehensive analysis and improved quality of medical services.

Research on methods and algorithms for encoding and compressing information in medical data is crucial for the development of modern medicine. They contribute to the improved efficiency of storing, transmitting, and processing medical data, ultimately enhancing the quality of healthcare services and improving patient outcomes. Further development in this area will ensure more efficient and secure use of medical data, which is an important step toward the digital transformation of healthcare.

Analysis of recent research and publications referenced by the authors. Digital image processing methods are discussed in the works of R.Gonzalez, R.Woods, B.Jeahne [3, 4], and methods of image compression are reviewed in [4–15].

Objective of the article. The goal of this article is to analyze methods of compressing video images with partial information loss for medical information and measurement systems to reduce their volume while maintaining quality.

Presentation of the main material.

Basic approaches to compressing video images with partial loss of information

Let’s consider the method of lossy image compression using specific types of images as examples, namely halftone and color images. We will provide definitions for these two types.

Images in which brightness changes continuously from white to black are called *halftone* or *multigradation* images. The signals of halftone images, unlike black-and-white facsimile, are analog. Therefore, for subsequent processing by a computer, they undergo discretization and quantization. The signals of a halftone image represent a two-dimensional function of brightness distribution $B(x, y)$ on a plane with coordinates x and y.

Images that are compressed are intended for perception by humans or for processing by automatic devices. If an image is encoded for transmission to a viewer, the volume of transmitted information can be reduced by utilizing the features of the human visual analyzer [3]. Since the accuracy of the human visual analyzer is limited, this allows some image distortions to be considered unnoticeable or insignificant. This feature enables the compression of the original image by losing some insignificant information, thus introducing some distortions. During decoding, the excluded information cannot be restored, and the image is recovered with some error. Different encoding methods introduce distortions of varying degrees. Therefore, when developing an image compression system, it is necessary to choose a transformation method that introduces the least noticeable distortions. Currently, most compression systems for black-and-white and color still and moving images are lossy systems. At the same time, there are areas of image processing using automatic analyzers where any loss of image information is unacceptable.

When designing and evaluating the effectiveness of image compression methods, it is necessary to have a reliable quantitative measure of image quality. Unfortunately, there is no analytical, objectively adequate measure of image quality for different image compression systems [3, 4]. Therefore, subjective quality assessment scales are used to characterize quality, presented in the form of a scale. There are two subjective assessment scales: the quality scale and the degradation scale. Typically, a five-point grading system is used. Each quality level on the scale characterizes the quality of the image being considered, taking into account a certain set of tested images. The degradation scale allows the assessment of the degree of distortion of the encoded image relative to the original image. Table 1 shows the quality and degradation scales adopted in image transmission technology.

Table 1

Scale of image quality and deterioration

Quality	**Rating in points**	**Deterioration**
Excellent	5	Inconspicuous
Good	4	Noticeable, but not obtrusive
Satisfactory	3	A little disturbing
Bad	2	Get in the way
Very bad	1	Very disturbing

The procedure for image quality assessment is carried out using the expert evaluation method. Before the experiment, experts are provided with an undistorted test image. During the experiment, the undistorted image is periodically shown, either replacing or placed next to the comparative image [5].

Two-dimensional image quality metrics are most often used in the assessment of compressed image quality, as they indicate the relative distortions of the encoded image compared to the original. The most common metric is the mean squared error, which represents the difference between the values of the corresponding pixels of the original and distorted images. Unfortunately, the mean squared error often poorly correlates with subjective image quality assessments [5].

In addition to the observer's visual evaluation, it is necessary to note the features of compression in the case of video information processing in automated systems. Let's consider the example of robotic vision systems. The modern development of automation tools is associated with the widespread use of robots and robotic technical complexes. In them, the presence of sensory means plays an important role. Sensory perception is the transformation of the relevant characteristics or properties of an object into information necessary for the device to perform a given target function. The sequence of perceiving the environment includes two stages: 1) converting the relevant properties of the object into signals; 2) processing, i.e., converting the signal into information necessary for the robot to plan and perform the target function. There is no and cannot be a complete analogy between sensory sensors and sensory organs. Sensory means, according to their principle of operation, can be divided into contact and non-contact. Non-contact systems can be conditionally divided into machine vision systems (MVS) and location-based sensory systems.

The main functions of MVS are:

- obtaining an image within the field of view;
- determining the presence of required objects;
- recognizing and isolating a specified object in the image;
- determining the coordinates of the object or its characteristic points relative to the coordinate system of the image sensor;
- forming control signals.

The development of MVS has allowed many modern production tasks to be solved on a fundamentally new basis. The task of pattern recognition is among those that are difficult to formalize. MVS can be built based on analog image processing. In the first case, the coordinates of the image elements and their color change continuously; in the second case, discretely. Analog image processing is carried out by optical systems. Digital image processing is performed using digital computers (personal computers), but there are also optical digital image processing systems.

MVS consists of a video camera that forms a video image, a device for inputting the video image into the computer, the computer itself, and a motion control device that allows the video camera to move in space. «Machine vision» systems are capable of completely replacing humans in production operations such as inspection, measurement, and object sorting.

Compression Based on Partial Exclusion of Color Information

Discrete cosine transform (DCT) for compressing RGB data is described in true colors. However, another approach is usually used. Instead, one step forward is taken initially, and before DCT, the amount of data is reduced by separating the color information from brightness and compressing it by forming special averaged values. Brightness information is compressed directly. The same approach is applied to chromatic images that contain only brightness information [4].

The method of compressing color information is called subsampling. It involves combining the color information for neighboring image elements. When applied correctly, this alone can reduce data volume by 50–60 % with minimal loss of quality.

As already mentioned, a color image contains both brightness and color information. However, in the RGB format, these informational components are not distinguished. Therefore, a transition to one of the other color systems, such as YUV, HSV, or YCC, is necessary.

Brightness information is much more important for image quality than color, since human vision reacts much more strongly to small changes in brightness than to small changes in color tone. Therefore, image compression in true colors can be achieved if full color information is not stored for each image element.

The first step in implementing this type of compression is always the transition of RGB values to the YUV or YCC system. This is necessary because in the RGB format it is impossible to distinguish brightness and color information. Suppose the transition is made to the YUV system. The Y value corresponds to the brightness of the image element. It is stored unchanged. In contrast, with 4:2:2 subsampling, the U and V values for four neighboring elements are summed, and only the average value is stored. This provides 6 bytes for 4 image elements, corresponding to 12 bits per image element. This simple method already ensures a 50 % reduction in the original data volume, and after reverse transformation to RGB values, the image quality loss remains minimal. The best quality is achieved if, after reverse transformation, the U and V values for all four elements are obtained not just identically, but by interpolation. For example, chromaticity (colorfulness) values for Photo-CD images are calculated using interpolation.

Even higher compression ratios are achieved with 4:1:1 subsampling. Here, the U and V values of eight neighboring image elements are combined. As a result, the data volume per image element is reduced from 24 to 10 bits. Consequently, the compression ratio slightly exceeds 58 %. However, in this case, small color distortions become noticeable. Higher subsampling coefficients almost always lead to obvious image quality losses and should be used only for moving images.

Storing video data with 4:2:2 subsampling can be performed using the interleaving method. For two image rows, the Y value is stored, followed by the subsampled U and V values. In contrast, according to the JPEG method, video data is stored not immediately after subsampling but is further compressed using DCT.

Transform-Based Video Image Compression

Transform-based coding is a procedure in which a video signal, held by PCM before transmission, undergoes some reversible transformation followed by quantization and coding. The purpose of the transformation is to concentrate all «important» coefficients in a specific area. Less significant coefficients of the transformed image are discarded, thereby reducing the volume of the original image. The compression ratio depends on the number of retained coefficients and can reach 10. The input signal S_z, representing digitized samples of image elements, is initially divided into blocks (fragments) of size $M \times N \times K$. Here, M and N are the number of image elements in a row and column respectively, and K is the number of image frames. For still images, $K = 1$.

Transform-based coding radically differs from classical coding methods such as PCM, predictive coding, or interpolation, which are applied directly to the video signal. Transform-based coding is an indirect method. The image undergoes unitary mathematical transformation; the obtained transform coefficients are quantized and coded for transmission through a communication channel. This method has established itself as an effective and practical means of coding monochrome, color, and multispectral images, including in real-time television systems.

The structural diagram of transform coding is shown in figure 1. The entire image or its regions, called fragments, undergo two-dimensional transformation. A typical image fragment consists of 8 × 8, 16 × 16, or 32 × 32 samples, although for some images it can be increased to 256 × 256. The choice of such fragment size is due to the fact that the correlation interval in images does not exceed 8 to 32 samples. Simultaneously, increasing the fragment size sharply increases the required memory volume and the processing time.

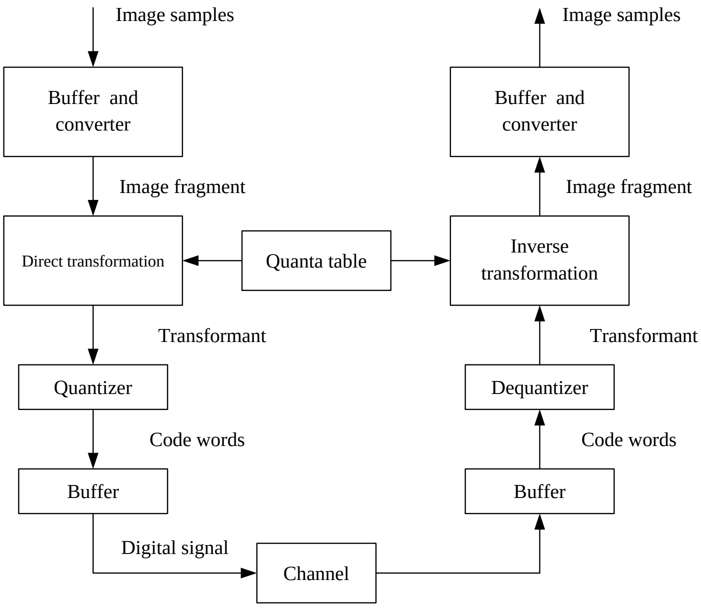

Fig. 1. Structural Diagram of Transform Coding

Fourier transform, cosine and sine transform, Hadamard, Haar, and Karhunen-Loeve transforms [3] are widely used in image compression. As a result of the transform, an uncorrelated series of numbers called transformants is formed. The number of relatively large transformants is insignificant, which allows them to be encoded much more efficiently than the information about the message itself [12].

The obtained transformants are divided for subsequent processing. The division is based on the zonal or threshold principle. In zonal division, only those transformants located in a previously designated zone (usually in the area of lower spatial frequencies) are selected, which significantly affect the subjective quality of the image. More precisely, a set of coefficients is highlighted that occupies some previously separated, fixed areas of the spectrum, usually corresponding to low-frequency components. Along analog communication lines, the values of the coefficients that fall into the selection zone are transmitted. When transmitting over digital communication lines, the values of the selected coefficients are quantized and assigned code combinations. The number of quantization levels is taken proportionally to the expected variance of the corresponding coefficient.

In the case of threshold division, transformants that exceed a certain threshold level are selected. Then, quantization and coding of some selected transformants are performed, and others are set to zero. By discarding some transformants, the original image is compressed. Inevitably, this leads to distortion of the transmitted message. Therefore, it is very important to exclude only those transformants that have little impact on the quality of the restored image. Quantization is the mapping of a continuous coefficient region into the region of their integer values, which are then converted into code words. Note that quantization is the second source of distortion in image compression since it is an irreversible process of transforming an analog source into its quantized equivalent. In some image compression schemes, the discarding of non-existent transformants occurs after the quantization process. Due to the necessity of informing about the location of the selected coefficients, threshold selection is used only for digital transmission.

All the advantages of image coding using transforms come from the peculiarities of energy distribution among the transform coefficients; thanks to these peculiarities, the two-dimensional spectrum of the image is more convenient for coding than the image in its original spatial representation. Due to the correlation connections between elements of a natural image, its spectrum energy tends to concentrate in a relatively small number of samples.

Quantization of transformants is performed in two stages:

1. The transformants are normalized by the measured variance, determined by estimating a large number of fragments;
2. The normalized transformants are processed by a quantizer, optimized for the given signal model.

The best method of image signal transformation, ensuring minimal mean square error, is the Karhunen-Loeve transform (K-L). In practice, this transform has not been widely used because its implementation requires knowledge of the static characteristics of the processed image ensemble. Moreover, there is no fast computation algorithm for this transform. The discrete cosine transform, which has a fast computation algorithm, is closest in efficiency to the K-L transform [14].

The discrete cosine transform (DCT) is related to the discrete Fourier transform. However, DCT works not with a two-dimensional signal (brightness B, time T) but with a three-dimensional one (image coordinates x, y, and brightness B). According to the DCT algorithm, the sequence of brightness samples of pixels is transformed from three-dimensional space into an identical representation in the frequency domain. In other words, the cosine transform converts spatial information into frequency (spectral) information. The x and y axes represent the spatial frequencies of the transformed signal in two different dimensions. The spatial frequencies of the image along coordinates x and y are determined by the number of black lines (separated by white gaps of the same length as the black line) in the image fitting into a segment of 1 mm, perpendicular to these lines along the direction of the x and y axes, respectively. Hence, spatial frequencies have the dimension мм$^{-1}$.

The discrete cosine transform is reversible, meaning that using inverse cosine transform, the signal is transferred from the frequency domain to the spatial representation. The cosine transform operates with a square matrix of brightness samples of image elements $B(x, y)$ of size $N \times N$ pixels. The result of the transform is a square matrix $N \times N$ of frequency coefficients (transformants) $F(i, j)$. The formulas for the forward and inverse DCT are respectively expressed by the following equations:

$$F(i, j) = \frac{1}{\sqrt{2N}} C(i) C(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} B(x, y) \cos\frac{(2x+1)i\pi}{2N} \cos\frac{(2y+1)j\pi}{2N}\ ; \tag{1}$$

$$B(x, y) = \frac{1}{2N} \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} C(i) C(j) F(i, j) \cos\frac{(2x+1)i\pi}{2N} \cos\frac{(2y+1)j\pi}{2N}\ . \tag{2}$$

Where $C(i)$ and $C(j)$ equal $1/\sqrt{2}$ for $i, j = 0$ and $C(i), C(j) = 1$ for $i, j > 0$; $B(x, y)$ is the brightness sample value of the image fragment pixel with coordinates x and y.

At first glance, the formulas seem quite cumbersome, but calculations based on them can be programmed using simple procedures. Individual expressions in these formulas can be replaced with simple tabular operations. The advantage of this transformation method is that it is reversible, statistically dependent elements become independent, and it allows the concentration of coefficients in one zone.

JPEG Compression Method

To generalize the experience of developing and using methods for compressing still halftone images and to develop an international standard, the ITU and ISO formed an organization in 1991, consisting of a group of experts named JPEG (Joint Photographic Expert Group). The algorithm standard for image processing developed by the commission was named JPEG, which defines the rules for compressing multigrade grayscale and color images. The standard consists of several parts, including both lossless data compression and compression with partial loss of transformable information. Lossless compression is based on DPCM with prediction, adaptive

Huffman, or arithmetic coding algorithms. Lossy image compression uses the cosine transform method followed by quantization [13].

The distortions introduced during information compression according to the JPEG algorithm should not lead to noticeable degradation of the quality of the restored image. Specifically, the image quality compared to the original should be rated as «excellent» or «good». Additionally, the method should be applicable to any multigrade images and be relatively easy to implement [13].

The structure of the video information compressor and decompressor according to the JPEG standard is shown in figure 2. It should be noted that it differs little from the transform-based compression scheme shown in figure 1.

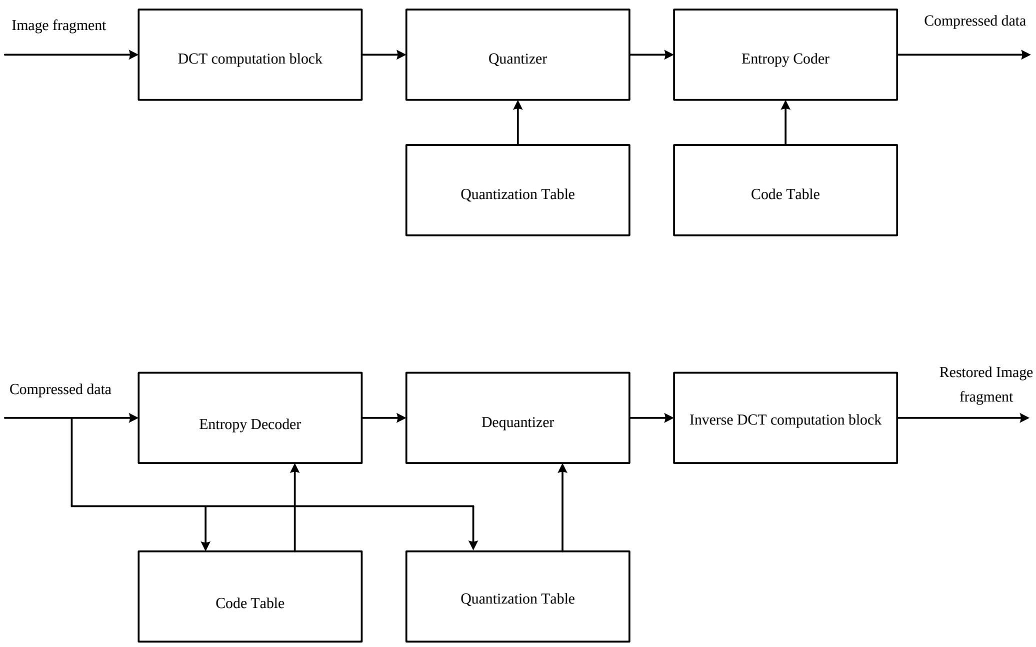

Fig. 2. Structural diagram of compressor and decompressor according to JPEG

DCT decomposes the image into amplitudes of certain frequencies. Thus, during transformation, we obtain a matrix where many coefficients are either close to zero or exactly zero. Additionally, due to the imperfections of human vision, coefficients can be approximated coarsely without noticeable loss in image quality.

For this purpose, coefficient quantization is used. In the simplest case, this involves an arithmetic bitwise right shift. During this transformation, some information is lost, but significant compression ratios can be achieved. Let's examine in detail some features of the JPEG image processing procedure. The encoded image is divided into blocks of size 8×8 elements (pixels). Each block represents a 64-point discrete signal consisting of a sequence of integers within the range $[0, 2^k - 1]$, which are later transformed into signed integers within the range $[-2^{k-1}, 2^{k-1} - 1]$. Thus, with 256 brightness gradations, the number of bits for encoding pixel intensities is $k = 8$. The pixel brightness, through scaling, is transferred from the interval $0 \div 255$ to interval from -127 to 127. In the block, the Forward Discrete Cosine Transform (FDCT) computes according to the expression:

$$\hat{B} = 3(B_A + B_C)/4 - B_B/2, \qquad (3)$$

The 64 coefficients of transformation (transformant) consist of sequences of integers within the range $[-2^{10}, 2^{10} - 1]$. Here, B-pixel, A, B, C are indices representing pixels. The output signal of the FDCT block is a 64-element array organized into a matrix 8×8. The amplitudes of the transformants are uniquely determined by the original block of video signal samples and represent coefficients at discrete frequencies. The coefficient at zero frequency determines the amplitude of the DC component, while other coefficients represent the amplitudes of the AC components. Due to the slight variation in image elements within the input block, the cosine transformation manages to group transformants in the lower spatial frequency domain. It is important to emphasize again that the cosine transform is reversible and does not lead to message compression; it only prepares data for the compression procedure performed by the quantizer.

The purpose of quantization is image compression by providing quantization accuracy no greater than necessary to achieve the desired image reproduction quality. During compression, the accuracy of transformants can be reduced, especially those further from the DC component located in the matrix with indices $(0,0)$. Decreasing the precision of transformant representation reduces the number of bits required for their representation. Elements closer to the DC component are encoded with more bits, while those further away are encoded with fewer bits.

In the JPEG algorithm, quantization is implemented using a quantization matrix. For each element of the transformant matrix, corresponding quantization values $Q(i, j)$ are present in the quantization matrix. Quantization is performed by dividing each transformant $F(i, j)$ by its corresponding quantization value $Q(i, j)$ and taking the integer part:

$$F_0(i, j) = [F(i, j)/Q(i, j)]. \tag{4}$$

The value $Q(i, j)$ ranges from 1 to 255. The magnitude of $Q(i, j) = 1$ provides the highest accuracy. As we move away from the top-left corner of the matrix, quantization values increase. It is easy to notice that for certain values, when $Q(i, j) > F(i, j)$ quantized value $F_0(i, j)$ becomes zero, indicating irreversible loss of information. The choice of quantization step size $Q(i, j)$ pixel-by-pixel determines the compression ratio and the quality of information restoration. Despite the presence of a standard quantization table, JPEG allows users some freedom to choose elements of the quantization matrix depending on the desired image restoration quality. In [5], it is proposed to determine quantization values using the formula:

$$Q(i, j) = 1 + (1 + i + j) \times \gamma, \tag{5}$$

where i, j are indices of elements in the quantization matrix, for $i, j = 1, 2, \ldots, N$; γ is the quality coefficient set by the user, recommended to be chosen within the range from 0 to 25. Larger quality coefficient values are also possible, but they significantly degrade the quality of the restored image. Table 2 presents a quantization matrix calculated according to (5) with a quality coefficient $\gamma = 2$.

During dequantization, multiplication is performed, i.e.

$$F'(i, j) = F'_0(i, j) \times Q(i, j). \tag{6}$$

Table 2

Quantum matrix with quantization coefficients $Q(i, j)$

j \ i	1	2	3	4	5	6	7	8
1	3	5	7	9	11	13	15	17
2	5	7	9	11	13	15	17	19
3	7	9	11	13	15	17	19	21
4	9	11	13	15	17	19	21	23
5	11	13	15	17	19	21	23	25
6	13	15	17	19	21	23	25	27
7	15	17	19	21	23	25	27	29
8	17	19	21	23	25	27	29	31

The value $F(i, j)$ is an input to the inverse cosine transformation. Table 3 provides examples of transform values at the output of the cosine transformation of an arbitrary image fragment, and table 4 provides the output values of the dequantizer.

Table 3

The value of the transformant before quantization

j \ i	1	2	3	4	5	6	7	8
1	92	3	-9	-7	3	-1	0	2
2	-39	-58	12	17	-2	2	4	2
3	-84	62	1	-18	3	4	-5	5
4	-52	-36	-10	14	-10	4	-2	0
5	-86	-40	49	-7	17	-6	-2	5
6	-62	65	-12	-2	3	-8	-2	0
7	-17	14	-36	17	-11	3	3	-1
9	-54	32	-9	9	22	0	1	3

Due to the fact that many transformants have zero values, the amount of information transmitted is significantly reduced.

The next step in JPEG processing involves encoding the quantized image. Initially, the transformants are divided into constant (DC) and variable (AC) components. The constant component of the transformant is a measure of the average value of the 63 samples of the image. Since neighboring image blocks typically exhibit strong correlation, the constant component of the next block usually does not differ much from the DC component of the previous block. It is transformed from an absolute value to a relative one, and then the increment of the current DC component relative to the previous one (DPCM) is applied.

The variable component transformants are converted into a sequence using the «zigzag» method. The sequence of transformants can be compressed using run-length encoding, Huffman coding, or arithmetic coding [4].

Table 4

The values of the transformants after dequantization

j \ *i*	1	2	3	4	5	6	7	8
1	90	0	-7	0	0	0	0	0
2	-35	-56	9	11	0	0	0	0
3	-84	54	0	-13	0	0	0	0
4	-45	-33	0	0	0	0	0	0
5	-77	-39	45	0	0	0	0	0
6	-52	60	0	0	0	0	0	0
7	-15	0	-19	0	0	0	0	0
8	-51	19	0	0	0	0	0	0

Disadvantages of JPEG include:

- presence of artifacts in reconstructed images, especially around object contours (critical for automated systems);
- poor reproduction of smooth transitions;
- manifestation of the structure of blocks (8 × 8 pixels) with strong compression and as a result – a large distortion of measurement video information with strong compression.

Advantages of the method:

- efficient compression by several tens of times;
- flexibility in choosing compression method parameters;
- availability of fast compression and decompression algorithms, allowing for quick computations.

Conclusions and prospects for further research. The article examines methods of compressing video images with partial information loss for medical information and measurement systems, based on partial exclusion of color information, transformation-based encoding, and the JPEG compression method. Their advantages and disadvantages are analyzed.

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Наукові інтереси:

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– метрологія, засоби вимірювання;
– системний аналіз складних технічних систем.

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– комп’ютеризовані інформаційно-вимірювальні системи;
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Аналіз методів стиснення відеозображень з частковою втратою інформації для інформаційно-вимірювальних систем медичного застосування

Важливою частиною інформаційно-вимірювальних систем та баз даних медичного застосування є інформація про стан пацієнтів, записана у вигляді відеозображень. Вони можуть бути сформовані у видимому діапазоні світлового випромінювання або бути записом результатів, отриманих у інших діапазонах випромінювань. Все це приводить до зростання обсягу медичних даних. Перехід від паперових до електронних записів також значно збільшив обсяг даних, які необхідно зберігати та обробляти. Ефективне зберігання такої інформації неможливе без зменшення її обсягу на основі процедур стиснення, в тому числі з втратою частини інформації. При цьому треба забезпечити викривлення, несуттєві для візуального сприйняття зображень, та незначні похибки результатів вимірювань інформативних параметрів відеосигналу. У цій статті розглянуто методи стиснення відеозображень з частковою втратою інформації для інформаційно-вимірювальних систем медичного застосування на основі часткового виключення інформації про колір і на основі кодування з перетворенням та метод стиснення JPEG. Проаналізовано їх переваги та недоліки.

Ключові слова: інформаційно-вимірювальна система; медичні діагностичні зображення; відеозображення; методи стиснення з частковою втратою інформації; JPEG-стиснення.

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