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HYPERSPECTRAL IMAGE COMPRESSION ALGORITHMS FOR PHYTOSANITARY INSPECTION OF AGRICULTURAL CROPS IN AEROSPACE PHOTOGRAPHY

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ABSTRACT

The article presents studies of hyperspectral image compression algorithms for phytosanitary control of agricultural crops in aerospace photography. The existing algorithms for lossless compression of hyperspectral images are analyzed. In this paper, we propose an algorithm for lossless compression of hyperspectral aerospace images, characterized by the use of a channel-by-channel difference linear regression transformation, which significantly reduces the range of data changes and increases the compression ratio due to this. The main idea of the proposed transformation is to form a set of pairs of correlated channels with the subsequent creation of transformed lossless blocks using regression analysis. This analysis allows you to reduce the size of the channels of the aerospace image and transform them before compression. The transformation of the regressed channel is performed on the values of the constructed regression model of the equation. The obtained results of comparing the transformed hyperspectral AI allow us to assume the effectiveness of using the stages of regression preorazing, which shows good results when calculating compression algorithms.

Keywords: *Hyperspectral aerospace images; Compression algorithm; Correlation; Regression analysis.*

1. INTRODUCTION

In remote sensing systems, the constant increase in the volume of information makes it difficult to process data, in which the complexity of the acceleration process appears, which is solved by improving data compression methods. The solution of this problem using compression methods provides: increasing the efficiency of managing complex technical systems by quickly obtaining important information from compressed data; reducing large streams of digital data; increasing the memory of output devices for recording information; increasing the channel bandwidth [1-2].

The urgency of the compression problem is associated with the correct preservation of information from hyperspectral images that use a significant memory size.

The importance of the compression problem is also related to the problem of correct storage of remote sensing data, since the existing methods of processing multispectral images for phytosanitary control do not provide more accurate data due to excessive information, it is proposed to use hyperspectral images, which have a number of advantages for determining diseases of grain crops.

The solution of this problem using compression methods provides: increasing the efficiency of managing complex technical systems by quickly obtaining important information from compressed data; reducing large streams of digital data; increasing the memory of output devices for recording information; increasing the channel bandwidth. The practice of using operational analysis of satellite data has shown their high efficiency in the tasks of information support of state bodies controlling agricultural production of the Republic of Kazakhstan.

According to the Food agriculture organization, diseases cause significant damage to agricultural crops and lead to significant crop losses in developed countries by 10%, and in developing countries by 20-50%. The development of diseases depends on many factors: seed quality, soil fertility, temperature, humidity, changes in technologies, reservators of primary infection, etc. One or two wet warm nights are enough to provoke the development of a fungus. Subsequently, if the weather is favorable, the disease spreads to other plants, to the upper leaves. Under the influence of the disease, the main indicators of the crop structure deteriorate in plants. Diseased plants significantly lose productivity, which affects not only the quantity, but also the quality of the resulting crop. Generally accepted methods of phytosanitary inspection are based on conducting a ground diagnosis of the disease by examining the field diagonally at an average of 10 points. This method is very time-consuming and expensive, which is impossible for large-scale farming. Therefore, it is important to have an automated solution for detecting these diseases.

Currently, the development of software systems for lossy data compression is an urgent task. In solving this problem, there are various areas of research in which research is actively conducted in the field of developing compression algorithms [1-18]. Lossy compression algorithms and methods cover a wide range of compression. Among them, the most common are orthogonal and wavelet transformations, the JPEG compression algorithm.

Researchers are very interested in the methods of compression of aerospace images with losses, which give significant results in the efficiency of the compression ratio, the use of orthogonal transformations: discrete-cosine transformation (DCT), discrete wavelet transform (DWT), SPIHT, prediction (prediction), JPEG, JPEG2000 and at the last stage entropy coding [20-21, 23-24].

Scientists Sujithra et al. [22] investigated the compression of hyperspectral aerospace images using DVP and Walsh-Hadamard transformation (WHT). A hybrid technology called Walsh wavelet transformation is proposed, consisting of four stages. At the first stage, two levels of fiberboard are applied, at the second stage, 2D-UAP are applied on each block of the low-frequency range (N=4). At the third stage, finding the values from the transformed subimages of each range, then they are compressed by arithmetic coding, this is the fourth stage. This technology provides a compression ratio of 1.8.

Indian researchers Keerthana, Poonam, Ramesh applied principal component analysis (PCA) to the compression of hyperspectral AI [25]. The hybrid compression method (DVP-TD) was used, which was effective because it provided detailed information about the spectral ranges of the image. DVP-TD using «global» encoding achieves a higher value of the "peak signal-to-noise ratio" (PSNR), shorter execution time and a high compression ratio of 8.0. The main disadvantage is that the PCA covariance matrix, which is used for decorrelation among frequency bands, should already be calculated, and therefore depends on the data. Therefore, it is necessary to reduce the computational load of the proposed method.

Scientists Cheng and Dill [26] improved Shapiro's EZW algorithm. Hybrid transformations consist in the Karhunen-Loève Transform (KLT), which decode the spectral data of hyper-perspectral aerospace images, and DVP is applied to spatial data. The proposed image compression has a compression ratio of 7.9. Disadvantages: wavelet coefficients can be scanned earlier than others in low-level subchannels; the basis of the encoder is the EZW Shapiro algorithm, encoding residual values and implementing only the dominant block; the algorithm is complicated by numerical efficiency.

Despite the great attention of researchers to the task of compressing hyperspectral AI, there is still insufficient research on compression methods that effectively increase the compression ratio [27-30]. Based on this, it follows that the proposed methods of accounting for interchannel correlation in compression algorithms do not take into account the basic fact that one or more consecutive subsets of hyperspectral AI channel groups with high spectral correlation may not have high correlation due to noise and other factors. Therefore, it is possible to use this fact in order to improve compression.

The purpose of the article is to describe a compression algorithm taking into account inter-channel correlation, characterized by data transformation with a decrease in the range of values of the initial values by forming a set of channel groups with high intra-group correlation of the corresponding pairs with the selection of optimal parameters. Improvement and obtaining an effective compression result can be achieved by:

- a new method of accounting for inter-channel correlation in the form of channel selection by grouping them and selecting the best correlated channel that determines the compression sequence;
- difference transformations obtained by the method of forming channel groups, which will allow storing data in a lower bit depth;
- a method of transformation in which the range of values of the original hyperspectral AI will change by forming additional data structures that are effectively compressed by entropy coding.

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2. TECHNOLOGY OF MONITORING AND PHYTOSANITARY CONTROL OF GRAIN CROPS

Among remote sensing technologies, the hyperspectral method has a number of advantages for detecting and monitoring diseases over a wide area. The fundamental principle of detecting infected plants is the analysis of the spectral reflection coefficient of electromagnetic radiation.

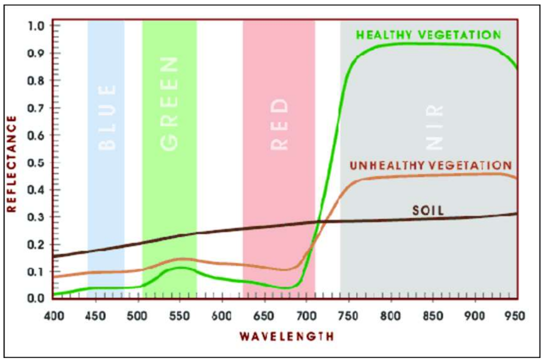


Figure 1: Spectral reflection coefficient of healthy and diseased plants

Plants under stress have a decrease in the reflection coefficient in the near infrared range (750-1300 nm) (Figure 1).

When shooting using remote sensing methods, the images have 3 types of resolution: temporal, spatial and spectral.

Time resolution refers to the frequency of surveys, for example, satellite images of the Landsat spectroradiometer cover the entire territory of the Earth every 16 days, MODIS (Tegga, Aqua) spectroradiometers take daily images, Sentinel satellites cover every every 5 days at the equator and every 2-3 days at mid-latitudes.

Spatial resolution refers to the minimum size of objects visible in the image. The spatial resolution depends on the satellite camera or the drone. So, lands at has the best resolution of 30m, MODIS-250m, and Sentinel-10m. With the help of a UAV, at a low shooting height, the spatial resolution reaches centimeters.

Spectral resolution refers to the range of the electromagnetic spectrum captured by the equipment. There are panchromatic photography, covering the entire visible spectrum in one black-and-white image, multispectral photography, presented as separate spectral channels (RGB and infrared channels), and hyperspectral photography with a large number of channels (Figure 2).

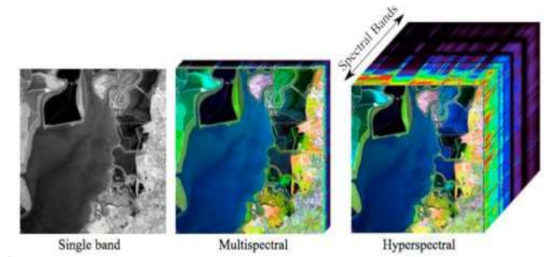
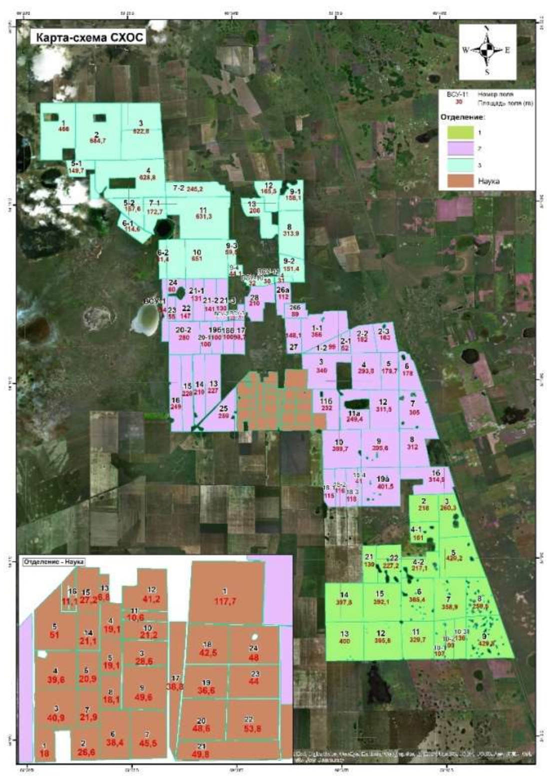


Figure 2: Spectral resolution of images

3. FIELD RESEARCH

Field studies were conducted on the territory of the North Kazakhstan Agricultural Experimental Station LLP (SHOS) of the North Kazakhstan region of the Akkaiyn district of the village of Shagalaly. In the scientific department of the farm, experimental plots were laid for 4 crops: sunflower, wheat, triticale, peas, flax (Figure 3).



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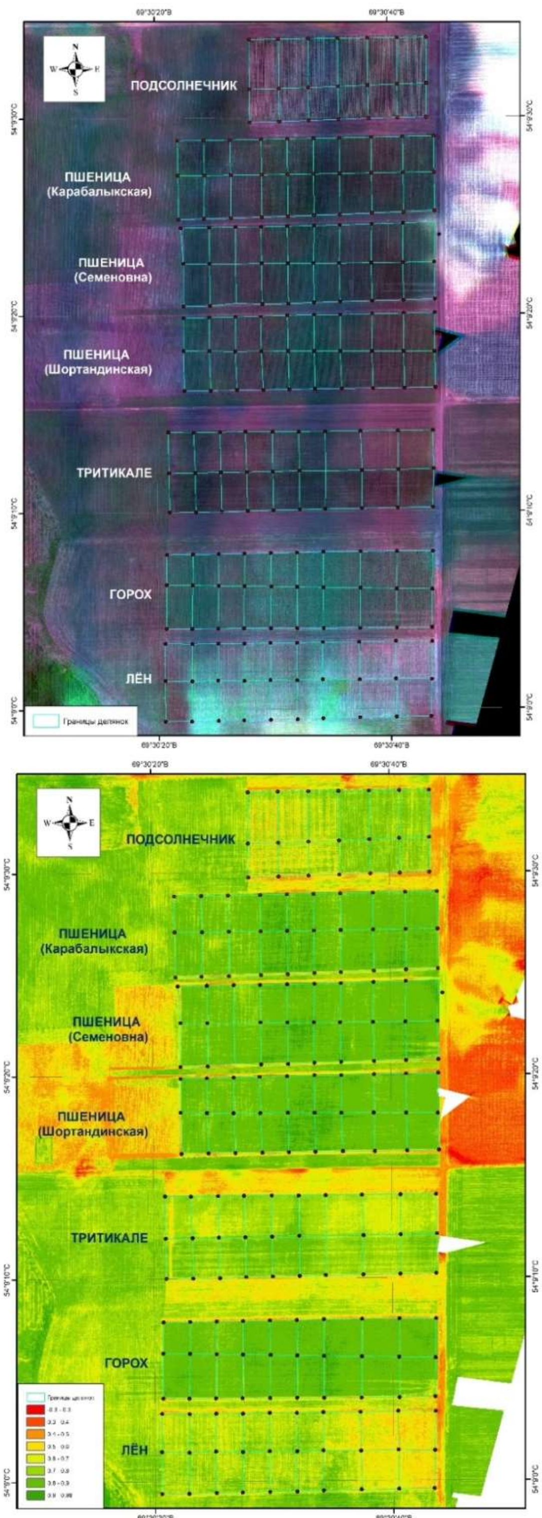

Figure 3: Map-scheme of ASCOS LLP and the research area (shooting with a Mamasense multispectral camera on the *left-RGB image, on the right NDVI-image 30-06-2021)*

Field measurements were carried out by ground and remote methods. Phytosanitary monitoring is based on visual diagnostics (Figure 4). Samples were taken to the laboratory to determine the type of diseases. In addition, a survey was carried out using the PSR 2500f field spectrometer using the ground method. The PCR2500 f makes it possible to shoot objects in the range from 350 nm to 2500 nm. The spectrometer was taken in direct contact with 15 measurements of each plant to determine the average spectral curve. After every 10 measurements, calibration measurements were carried out on a white calibration panel coated with BaSO4. The survey is carried out in clear weather from 11.00 to 17.00.

Aerial photography of test polygons was carried out using a GAIA 120 UAV with a Headwall Nano hyperspectral camera (Figure 5).

Figure 4: Ground surveys of diseases of agricultural crops (sunflower on the left, wheat on the right)

The Headwall Nano Hyperspec Hyperspectral camera allows you to collect a series of continuous, very narrow spectral bands, providing an almost continuous spectrum of an object, commonly referred to as a spectral signature. This method has a number of advantages compared to more traditional multispectral sensors, in which several relatively wide ranges are implemented. While multispectral sensors typically consist of 5-12 bands, hyperspectral sensors can contain hundreds of bands, with a bandwidth typically in the 5-20 nm range. The advantages of quantifying the spectral characteristics of an object or material are recognized and used in phytosanitary control for the identification of landings, and their application in various disciplines covering plant sciences for the production of plant pigment, biochemistry and evaluation of various plant species, geology for mineral exploration and

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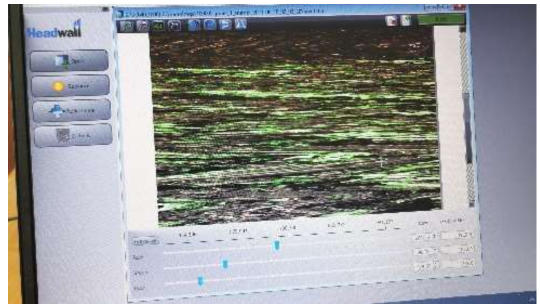
marine sciences for water quality assessment and mapping of benthic communities, among many others. The usefulness of hyperspectral sensors has been enhanced by relatively recent developments in the use of unmanned aerial vehicles (UAVs) as an observation platform. Thanks to developments in the field of sensor miniaturization, power supply stability, communication and storage requirements, the use of unmanned aerial vehicles for hyperspectral remote sensing has become a possible option for obtaining hyperspectral data of ultra-high spatial resolution. Hyperspectral sensors based on unmanned aerial vehicles can be broadly divided into several groups.

Application of the Headwall Nano Hyperspec hyperspectral camera, which has 270 channels per 640 spatial pixels in the range from visible to near infrared from 400 nm to 1000 nm. Thus, it is necessary to develop a mathematical apparatus and algorithms for compressing hyperspectral Headwall Nano Hyperspec data.

The shooting was carried out at an altitude of 50 m, with a flight speed of 4-5 m/s. The flight is carried out in automatic mode according to a pre-created flight plan in the UgCS application (or any other for controlling the drone). Before shooting with a hyperspectral camera, calibration is performed in the HyperSpec application on a white calibration panel and a picture is taken with the lens closed for subsequent processing.

As a result of shooting, each image forms 270 images of the electromagnetic spectrum, which require pre-processing of converting images into spectral reflection.



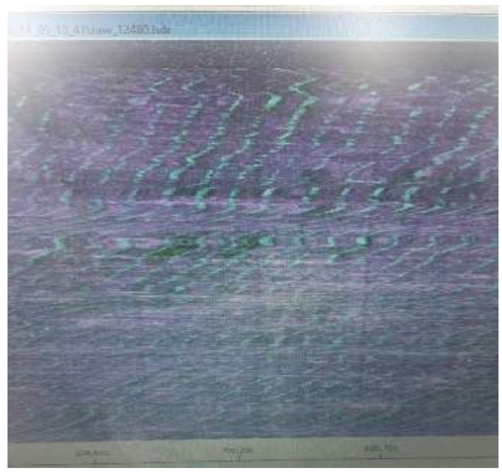


Figure 5: Shooting with a GAIA 120 UAV with a Headwall Nano camera

4. METHODS AND ALGORITHMS

4.1 Pre-processing

Pre-processing includes: radiometric calibration and orthotransformation of images.

Radiometric calibration is the process of translating the values of the output signal of the survey device and their translation into absolute albedo values. It is performed automatically in the program for processing images using calibration images taken before the flight (Figure 6).

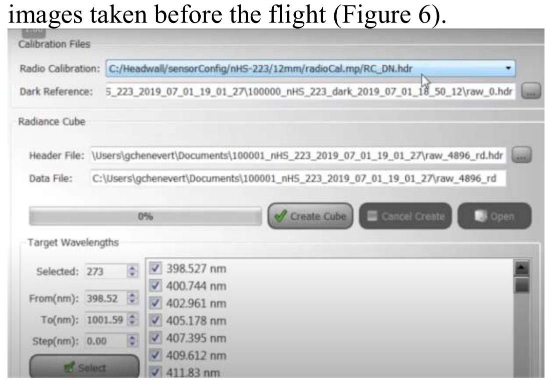


Figure 6: Radiometric calibration of images in Spectral View

Orthotransformation of images - the process of geometric image correction, which

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eliminates perspective distortions, reversals, distortions caused by lens distortion, was carried out in Spectral View (Figure 7).

Figure 7: Orthotransformed snapshot

The digital terrain model for orthotransformation is taken from SRTM data (https:/srtm.csi.cgiar.org).

When the push broom sensor is directly attached to the UAV body, every small change in pitch, roll and yaw made by the autopilot to maintain the programmed flight path is recorded in the data. Installing the push broom linear scanner on a stabilized gimbal can reduce the geometric noise in the data caused by the movements of the UAV. In our case, the sensor was not installed on a stabilized gimbal, which significantly affected the geometric correction of the images.

The camera installed on the UAV allows you to collect data with a very high spatial (and temporal) resolution. However, to link images to a geographical location, additional equipment is required, such as satellite/inertial navigation System (GNSS/IMU) sensors and data logging units, since the process of collecting data from the push broom sensor is sensitive to flight dynamics, and orthotransformation is a complex procedure.

Undoubtedly, hyperspectral remote sensing based on unmanned aerial vehicles is a convenient alternative to traditional space and aviation platforms, especially for mapping small areas and frequent monitoring, providing both high spatial and temporal resolution.

4.2 Compression algorithm for hyperspectral images

Despite a fairly long period of research, the problem of compressing hypespectral data has not yet received a final solution, but in recent years there has been significant progress and some improvements in this direction. Some compression methods already provide sufficient quality of the restored images, but their development did not take into account the need to reduce and optimize the computational complexity of the algorithms used [7-11]. This limits the possibilities of their application in real-time systems. Increasing the compression ratio and high quality are the main criteria for efficiency in image compression.

To solve this problem, the following approaches and scientific research methods will be used:

- taking into account the spectral correlation, which gives certain advantages based on the calculated correlation matrix and regression analysis [12-15];
- discrete-cosine transformation with high quality and minimal loss of hyperspectral data;
- evaluation of the quality criteria of the restored PSNR, MSE, PMSE, etc. GI for lossless compression;
- adaptive arithmetic coding, the introduction of which will improve the results of compression, since it is one of the best among statistical methods;
- the use of parallel compression algorithms to reduce the cost of computer computing resources.

The lossless compression algorithm, taking into account inter-band correlation and regression analysis, will increase the compression ratio by more than two times compared to using universal archivers. The proposed algorithm for finding the best groups of channels at a given correlation value will increase the efficiency of using the channel subtraction stage (difference transformation).

The sequence of processing stages and the compression algorithm:

1) calculation of the correlation value between all pairs of hyperspectral image channels and determination of the channel encoding and decoding sequence;

2) regression transformation algorithm;

3) obtaining channel differences and their block-by-block transformation;

4) compression by a statistical algorithm.

Description of the lossless compression algorithm.

Step 1. Let's calculate the values of the correlation matrix between all pairs of AI channels, while identifying the most correlated groups of channel pairs. Based on the matrix, we will form and determine the sequence of transformation

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(encoding) and inverse transformation by constructing a strongly branching tree.

Step 2. Regression analysis based on step 1. We calculate the linear regression coefficients between the values of the generating (main tree vertex, BI) and the regressed (RI) channels of hyperspectral AI by creating optimal values for forming arrays of differences between BI and RI.

Step 3. Block-by-block conversion. The idea of the transformation is to calculate the differences based on step 2 by the block-by-block separation of hyperspectral data. The effectiveness of this separation is that the differences obtained do not cover the entire range of the image, but only a certain block. Due to this, they are effectively compressed by an entropy algorithm.

Step 4. Compression by a well-known statistical algorithm.

Let's consider the proposed algorithm in detail. From the second channel, we extract a sequence of samples that are located in the matrix at the same positions as the samples from the first channel. We denote the obtained sequences with the letters x and y, and the unit values are xi and yi (i from 1 to m inclusive). Also, the formula will need the arithmetic mean values of both sample sequences.

$$\bar{x} = \frac{1}{m}\sum_{i=1}^{m} x_i \,, \bar{y} = \frac{1}{m}\sum_{i=1}^{m} y_i$$

Now can apply the formula:

$$r = \frac{\sum_{i=1}^{m}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{m}(x_i - \bar{x})^2 \sum_{i=1}^{m}(y_i - \bar{y})^2}}$$

Why we extract samples – for large channel matrices, calculating the formula for all values would take a huge amount of time. By setting the upper threshold for the number of samples, we remove the dependence of the calculation time on the image size.

Calculating the coefficients for all possible pairs of channels of the same image, we build a sequence of encoding-naturally, starting from large values to smaller ones.

Regression transformation

The essence of the transformation is to match a certain structure to the encoded pair of channels, which would:

1) allowed to unambiguously restore one of the original channels according to the data of another channel,

2) took up as little disk space as possible.

To do this, the following algorithm was defined. In each encoded pair of channels, we define a generating channel (master) and a regressed channel (slave, compressible). It has been experimentally confirmed that the principle of determination has a rather insignificant effect on the compression index; therefore, without wasting time on sorting through both options, we choose the channel with a smaller index as the generating channel (assuming that all channels were originally numbered).

Now will explain how the difference matrix is considered (later it will be clear why the desired structure is so named). Before that, we calculated the linear correlation coefficient. The idea of linear regression in our case is to find such real values of k and b such that the matrix formed from the data of the encoded pair according to the following formula:

$$d_{ij} = \left(x_{ij} * k + b\right) - y_{ij},$$

(here after xij and yij are the values in the master and slave matrices, respectively)

it would have the smallest possible values in itself. Next, we will call the matrix d with the values of dij the "difference matrix". A sufficiently good linear correlation indicator (close to one), calculated beforehand, leads to sufficiently low values of dij. Knowing the values of k, b and the matrix d, we can restore the matrix y from the values of the matrix x:

$$y_{ij} = \left(x_{ij} * k + b\right) - d_{ij}$$

Standard formulas used for calculating linear regression parameters:

$$k = \frac{\overline{xy} - \bar{x} \times \bar{y}}{\overline{x^2} - (\bar{x})^2}, b = \frac{\overline{x^2} \times \bar{y} - \bar{x} \times \overline{xy}}{\overline{x^2} - (\bar{x})^2},$$

where:

$$\bar{x} = \frac{1}{i \times j}\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \,;\; \bar{y} = \frac{1}{i \times j}\sum_{i=1}^{m}\sum_{j=1}^{n} y_{ij} \,;$$

$$\overline{xy} = \frac{1}{i \times j}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij} \times y_{ij}\right); \overline{x^2} = \frac{1}{i \times j}\sum_{i=1}^{m}\sum_{j=1}^{n} {x_{ij}}^2$$

(*m* is the height of the image, *n* is the width).

In each compressed channel, we put the values k and b in Double format (8 bytes, 15 decimal places in decimal format). By encoding the only main generating channel for the image (the generating channel of the first pair) independently of the others, we will be able to restore it later in the first place, then gradually restore all the other compressed channels (as mentioned earlier, through the coefficients k and b).

The absence of losses is ensured during transformations. After obtaining the matrix d and before writing it to the file, we round the values to the nearest integer (in the case of a fractional part equal to 0.5 – to a smaller integer). This does not prevent you from performing a lossless recovery. Let's explain why. Let's pay attention to the formula:

$$d_{ij} = \left(x_{ij} * k + b\right) - y_{ij}$$

The matrices x and y are integer, so the value $w_{ij} = \left(x_{ij} * k + b\right)$ it has the same fractional part (let's denote it q) as the number d_{ij} before rounding. We will denote the integer part of the numbers through square brackets, the fractional part through curly ones. So, $q = \{d_{ij}\} = \{w_{ij}\}$.

After rounding, the rounded values are written to the difference file d_{ij} .

Moving on to recovery:

$$y'_{ij} = \left(x_{ij} * k + b\right) - d'_{ij} = \left(d_{ij} + y_{ij}\right) - d'_{ij}.$$

The value of w_{ij} remains unchanged, since k and b were calculated earlier and written in Double format (that is, lossless), the values of x are integer and do not undergo losses.

If q <= 0.5, then $d'_{ij} = [d_{ij}]$ and:

$$y'_{ij} = \left(d_{ij} + y_{ij}\right) - d'_{ij} = q + y_{ij}$$

So, rounding up y'_{ij} we get the original value y_{ij}

If q > 0.5, that $d'_{ij} = \left[d_{ij}\right] + 1$, and:

$$y'_{ij} = \left(d_{ij} + y_{ij}\right) - d'_{ij} = q + y_{ij} - 1 = y_{ij} - (1 - q)$$

The value (1-q) < = 0.5, and y_{ij} is an integer. This also means: rounding y'_{ij}, we get the original value of y_{ij}.

Thus, the regressive transformation does not incur losses. To reverse decode hyperspectral AI, we perform the following actions:

Step 1. Decoding arrays of differences by the Huffman algorithm.

Step 2. Forming regression transformation arrays by finding the sums between the generating channel and its average value.

Step 3. Formation of initial arrays based on the available OHR coefficients and obtaining the initial data of hyperspectral AI.

5. EXPERIMENTAL RESULTS

In Figure 8-9 present compression algorithms with a variable number of channels *K* and a geometric size *R* (100×100) in comparison with the universal archivers *Winrar*, *7Z* and the specialized *JPEG* Lossless algorithm. The compression ratio indicators are 75 percent or more higher than universal algorithms, due to the consideration of inter-channel correlation, regression and difference transformation.

As a result of experiments, the groups with the highest correlation were determined based on the algorithm described in [10-14]. In which the compression ratio varies from 5 to 8. This suggests that taking into account the inter-channel correlation for hyperspectral AI is crucial in the compression problem.

To speed up the calculation of intermediate calculations, multithreaded processing was applied, in which certain results were obtained when compressing AI. Figure 10 shows a graph of the calculation time of the experiment in comparison with universal archivers and the JPEG Lossless algorithm. It can be seen that the dependencies of the compression ratio of the algorithms, taking into account the correlation and grouping of channels, are higher than if all 270 channels are fed to the input. This means that subtraction (difference transformations) using regression analysis are effective when selecting certain groups of channels, then the values of the differences will be the smallest, which will allow you to store the original channels in the smallest amount on disk.

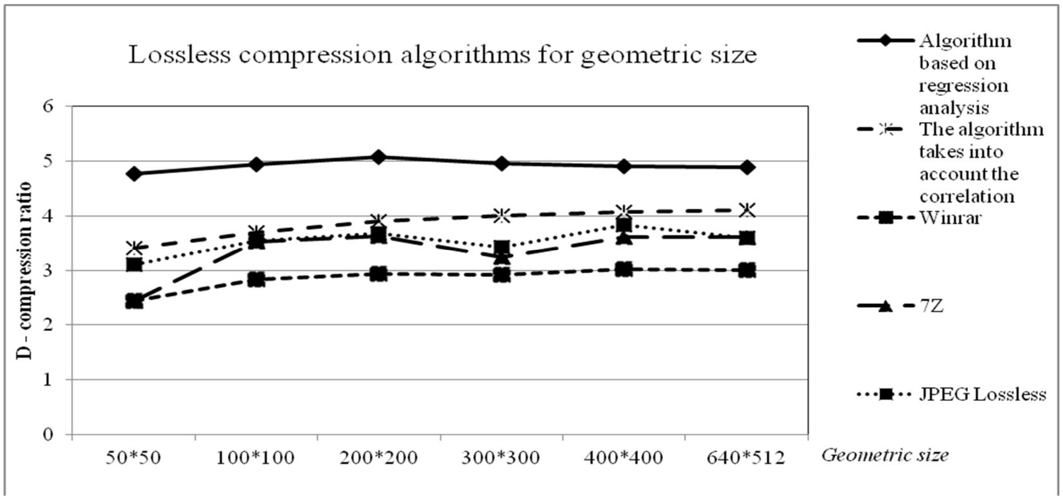

Figure 8: Comparison of algorithms by the number of channels

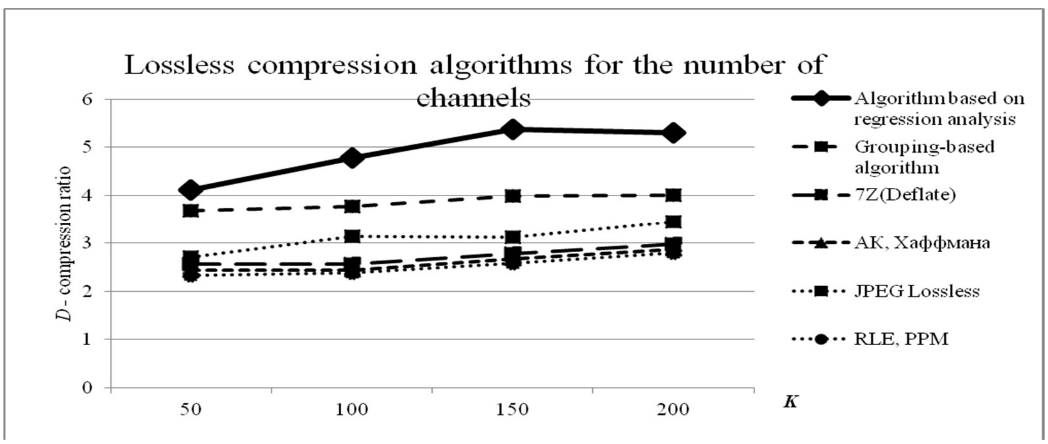

Figure 9: Comparison of algorithms for the geometric size of images

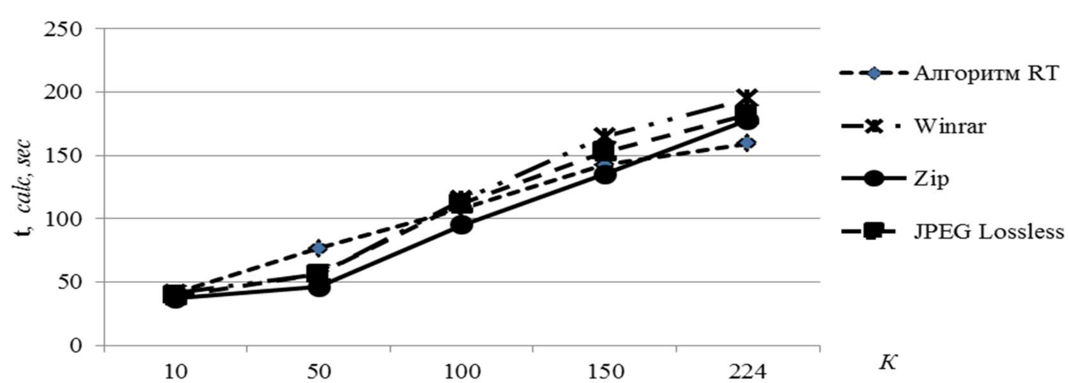

Figure 10: Comparison of compression algorithms by calculation time

6. DIFFERENCE FROM PRIOR WORK

The results obtained during the research allow us to determine the optimal parameters for compression, which differ significantly from previous works:

1. The results of the compression ratio indicators improve with an increase in the size of the channels of parameter R. This is due to the fact that the more values to be converted, the fewer bits are required to store them.

2. Taking into account the inter-channel correlation of the parameter With or shows that the greatest values in the compression ratio of the channel number, at 170 > N > 0.

3. Algorithm taking into account correlation and grouping at N=[2..10] shows the most effective growth in the compression ratio due to the formed groups of channels and their ordering.

The novelty of the research article lies in the development of an algorithm for compressing hyperspectral aerospace images taking into account inter-channel correlation, characterized by data transformation with a decrease in the range of values of the initial values by forming a set of channel groups with high intra-group correlation of the corresponding pairs with the selection of optimal parameters, which allows to increase the compression ratio compared with analogues.

7. CONCLUSION

The lossless compression algorithm, taking into account inter-band correlation and regression analysis, allows you to increase the compression ratio to (D>8) than in the use of universal archivers.

The proposed approach to finding the best groups of channels at a given correlation value increases the efficiency of using the difference transformation stage.

The obtained experimental results show the effectiveness of using the stages of regression transformation and parallel processing, which allow us to obtain advantages over analogues.

The proposed approach to the formation and ordering of a set of channel groups with high intra-group correlation has increased the effectiveness of the channel subtraction stage (difference transformation);

The obtained results of comparing the transformed hyperspectral AI with archivers and JPEG2000 Lossless allow us to assert the effectiveness of the indexed conversion method.

The conducted experiments have shown the ability of these algorithms to compress images of remote sensing of the Earth with a compression ratio of 5.78. The developed algorithmic and software can be integrated into the ground and on-board systems of aircraft to improve operational characteristics and reduce the occupied disk memory.

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