Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

DOI: 10.37943/18BIAC9844

Assiya Sarinova
PhD, Associate Professor, Department of Intelligent Systems and Cybersecurity
a.sarinova@astanait.edu.kz, orcid.org/0000-0003-4254-376X
Astana IT University, Kazakhstan

Alexandr Neftissov
PhD, Associate Professor, Research and Innovation Center "Industry 4.0"
Alexandr.neftissov@astanait.edu.kz, orcid.org/0000-0003-4079-2025
Astana IT University, Kazakhstan

Leyla Rzayeva
PhD, Associate Professor, Department of Intelligent Systems and Cybersecurity
l.rzayeva@astanait.edu.kz, orcid.org/0000-0003-4254-376X
Astana IT University, Kazakhstan

Alimzhan Yessenov
Senior Lecturer, Department of Intelligent Systems and Cybersecurity
a.yessenov@astanait.edu.kz, orcid.org/0009-0006-8997-3926
Astana IT University, Kazakhstan

Lalita Kirichenko
Junior Researcher, Research and Innovation Center "Industry 4.0"
lalita17021996@gmail.com, orcid.org/0000-0001-7069-5395
Astana IT University, Kazakhstan

Ilyas Kazambayev
Junior Researcher, Research and Innovation Center "Industry 4.0"
ilyaskazambayev@gmail.com, orcid.org/0000-0003-0850-7490
Astana IT University, Kazakhstan

DEVELOPMENT OF AEROSPACE IMAGES PRELIMINARY PROCESSING METHOD FOR SUBSEQUENT RECOGNITION AND IDENTIFICATION OF VARIOUS OBJECTS

Abstract: Nowadays, the application of hyperspectral images is vital for every section of the humanity life such as agrotechnical research for the field condition state and water security. This article presents a new lossless data compression algorithm focused on the processing of hyperspectral aerospace images. The algorithm takes into account inter-band correlation and difference transformations to effectively reduce the range of initial values. correlation allows you to find the best reference channel that defines the sequence of operations in the algorithm, which contributes to a significant increase in the compression ratio while maintaining high data quality. The practical implementation of the algorithm lies in the process of the transfer the lower size file with high efficiency for unmanned aerial vehicle and satellites to save more computational resources. This method demonstrates high computational efficiency and can be applied to various tasks that require efficient storage and transmission of hyperspectral images. The importance of processing hyperspectral data and the problems associated with their volume and complexity of analysis were described. Current approaches to data compression are considered and their limitations are identified, which justifies the need to develop new methods. The relevance and necessity of effective compression algorithms

Received: 10.06.2024 Accepted: 25.06.2024 Published: 30.06.2024

for aerospace applications is emphasized. An analysis of existing methods and algorithms for compressing hyperspectral data was carried out. Particular attention is paid to approaches that use cross-channel correlation and difference transformations. The effectiveness of current methods is evaluated and their shortcomings are identified, which serves as a justification for the development of a new algorithm. A developed lossless data compression algorithm based on the use of inter-band correlation and difference transformations was described. The stages of forming groups of channels and the selection of optimal compression parameters are considered in detail. The method of determining the reference channel, which sets the sequence of operations in the algorithm, which provides more efficient data compression, is especially noted. The advantages and possible limitations of the new approach, as well as its potential for practical use, are discussed. It was noted that the developed method successfully solves the problems associated with the volume of hyperspectral data, providing a high compression ratio without quality loss. The prospects for further development of the algorithm and its application in various fields of science and technology are discussed.

Keywords: data compression, hyperspectral images, interband correlation, difference transformations, lossless, compression algorithm.

Introduction (Literary review)

At present, obtaining information using satellite images, as well as images from unmanned aerial vehicles, is an integral part of any monitoring system. Moreover, images are of various types, one of the most common is hyperspectral. However, the process of transferring image data is difficult and has a large loss that can be reduced by various methods. For example, the SBSS technique, which is used to efficiently extract hidden information from hyperspectral images, its main assumptions are: 1) intelligently combine spectral and spatial information to extract the intrinsic properties of a hyperspectral image; 2) there are some output bands capable of presenting a hyperspectral image without significant loss of information when using the data; and 3) there is an intrinsic relationship between the output, the scale, and the description of the image. The computational complexity of the SBSS method is linear, and experimental results show that the proposed method achieves competitive results compared to other advanced frequency band selection methods in terms of classification accuracy [1].

On the other hand, band selection is an effective method to reduce redundancy in a hyperspectral image (HIB) without compromising the original content. Typically, popular band selection methods use strong assumptions, such as linear or nonlinear assumptions with simple predefined cores, to model correlations between bands. However, such strong assumptions may not be valid in a real-world environment due to the complex interactions between the bands. In this letter, we consider the selection of hyperspectral image bands as a problem of spectral reconstruction. Assuming that the HSE can be sparsely reconstructed from multiple informative bands, we propose an attention-based autoencoder to model the basic nonlinear relationships between bands. The proposed model consists of two parts: an attention module and an autoencoder. The attention module is used to create an attention mask that selects the most informative bands for each pixel. The autoencoder uses these informative bands to restore the original GSI. The final selection of the bands is done by clustering the columns of the attention mask and identifying the most representative band for each cluster. Unlike most existing methods for selecting bands, the proposed method directly studies global nonlinear correlations between bands without strong assumptions. The proposed model is easy to implement, and all parameters can be co-optimized using the stochastic gradient descent algorithm. Experiments on three open public datasets show that the proposed method offers promising results [2].

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

The band selection algorithm proposed in [3] begins with the assessment of redundancy through the analysis of relationships between spectral bands. The spectral bands are then ranked according to their relative importance. Further, to efficiently remove redundant spectral bands and preserve the original information, the optimal band combination is constructed as a maximum linearly independent subset. The following can be highlighted: Proposal of a new strategy for the selection of strips, which is primarily aimed at preserving the original information; Development of a representation algorithm with a non-negative low rank to identify internal relationships between spectral bands; Introduction of an intelligent strategy for adaptive determination of the optimal combination of spectral bands. To test the efficacy, experiments were carried out both in hyperspectral decomposition and in classification. In decomposition, the proposed algorithm reduces the mean square errors by 0.05, 0.03, and 0.05 for the Urban, Cuprite, and Indian Pines datasets, respectively. In terms of classification, our algorithm achieves overall accuracy of 77.07% and 89.19% for the Indian Pines and Pavia University datasets, respectively. These results are close to performance using the original images. Thus, comparative experiments not only demonstrate the superiority of the proposed algorithm, but also confirm the expediency of choosing strips in the processing of GSI.

Another possible solution is a hyperspectral image classification (HSIC) approach called Progressive Band Selection (PBSP-HSIC) [4]. This method performs classification in several stages, selecting specific subsets of bands at each stage, providing a unique perspective on how different classes are classified gradually. The main benefits are improved classification accuracy: PBSP-HSIC shows improved accuracy compared to traditional HSIC methods, gradual processing, efficient band selection: prioritizes bands important for the classification of certain classes, potentially reducing the computational burden. The disadvantages are the complexity of implementation, the risk of overtraining, and dependence on the initial choice of lanes. PBSP-HSIC represents a novel and potentially more efficient approach to the classification of hyperspectral images, albeit with some implementation challenges and overfitting risks.

It is also possible to use the method of classification of hyperspectral images, using data augmentation and classification merging [5]. This approach aims to solve the problem of a limited number of labeled samples in hyperspectral image classification. The advantages are increased accuracy, resistance to limited data, and effectively solves the problem of overfitting when working with a limited number of labeled samples. In turn, the solution has such disadvantages as complexity, dependence on data growth, and the risk of overtraining if used incorrectly. In general, the solution is especially useful in scenarios with a limited amount of labeled data, although it requires careful implementation.

On the other hand, in the paper [6], a new convolutional neural network (CNN) architecture for hyperspectral image classification (HSIC) was proposed, called Attention-Based Dense CNN (FADCNN). This network integrates spatial spectral characteristics using a dense CNN structure and introduces an attentional feedback mechanism to improve feature extraction. The solution has better classification accuracy than other best practices, a feedback attention mechanism that helps extract more discriminative features, and the architecture is resilient to HSIC-related challenges. However, it is worth considering that the architecture is complex due to the integration of dense CNN and attention feedback mechanisms, performance is sensitive to the initial configuration. FADCNN introduces an innovative approach to HSIC, offering significant improvements in classification accuracy and feature extraction, although it comes with challenges related to complexity and implementation.

It is possible to use the architecture of a convolutional neural network based on capsule networks for the classification of hyperspectral images [7]. This approach aims to improve traditional CNNs by making better use of the relationships between hyperspectral image features. The solution has better classification accuracy, uses capsule networks to improve the use of feature relationships, and effectively solves the problems of high data complexity. However, the architecture is more complex than traditional CNNs, performance can be sensitive to initial settings, and despite improvements, the approach can be computationally intensive. In general, capsule networking is being used to improve performance, although it comes with increased complexity and computational requirements.

According to [8], the use of low-power architectures, especially on the NVIDIA Jetson Tegra TX2 device, for the classification of hyperspectral images using deep learning models, shows that low-power architectures are more efficient and suitable for remote sensing applications, underscoring the practicality of such architectures. However, it is worth noting that data processing is slower, the trade-off between performance and power consumption, and limitations in memory and device power. In conclusion, the article provides valuable insights into the feasibility of using low-power architectures for efficient processing of hyperspectral images, highlighting their advantages in energy efficiency and practicality, as well as considering the trade-offs in processing speed and hardware capabilities.

It is possible to use an unsupervised method of adapting domains for the classification of hyperspectral images, focused on improving classification performance under noisy labeling conditions [9]. Benefits include improved tolerance to noisy labels, efficient domain adaptation, and unsupervised learning. Disadvantages include the complexity of the method, dependence on noise modeling, and the risk of overfitting. This method represents a significant contribution to the field of hyperspectral image classification, especially in the context of working with noisy labels.

It is possible to use a method for the classification of hyperspectral images, focusing on resistance to noisy labels and effective domain adaptation [10]. The method operates in unsupervised mode and is designed to solve the problems of noisy data in hyperspectral imaging. The benefits include improved resilience and efficient adaptation between different domains, while the complexity of the method and the dependency on noise modeling present challenges. The approach represents a significant contribution to the field of hyperspectral image classification, especially in the context of working with noisy labels under conditions of unsupervised domain adaptation.

In the modern world, there are many different solutions to improve the efficiency of compression of hyperspectral images, one of which is the methods of noise suppression by spatial preprocessing [11]. First of all, image processing is carried out using the HySime algorithm, which allows you to reduce losses in the process of transferring information for processing. As a result, the image undergoes spatial spectral preprocessing, during which the HySime algorithm is also used to correct the flow of information. Then, a clean material is selected from a set of pixels using endmember extraction algorithms (EEA). Then, to ensure accuracy, Fully constrained least square (FCLS) is used, which compares the flow of information from the resulting drawing to the reconstruction process, which is carried out on the basis of the root mean square error. As a result, the spectral angular distance is cropped. The anomalous endmembers are then added to the matrix obtained after the EEA. On the basis of the resulting matrix, the following reconstruction is carried out. A novelty in this solution is the use of improved EEAs, which allow noise to be eliminated, which has been demonstrated to reduce error. Similar to this method, a solution [12] that proposes fast GPU-based preprocessing can also be considered. This method is structurally built like any traditional method of spatial preprocessing, but using such video cards as the GeForce GTX 580, GeForce GTX870M, which made it possible to determine the optimal architecture for video cards that perform preprocessing. It should be noted that this approach allows us to consider the method of fast preprocessing, and, in the future, it is possible to build solutions on programmable logic integrated circuits (FPGAs), which will simplify the preprocessing process and reduce the resources

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

required for information transmission. Another such method is the use of geodesic and spatial Euclidean weights of adjacent pixels for hyperspectral Endmember Extraction preprocessing [13]. The advantage of this approach is that it simplifies the image processing process, but the disadvantage is that it complicates the pre-processing process. However, the process of calculating errors and corrections is complex and requires a lot of resources.

Therefore, the purpose of this study is to offer a simpler method for preprocessing images. The prerequisites for this work are the works in which methods for improving the efficiency of image transmission were considered [14].

Methods and Materials

In order to develop the method, the main methods and means of such fundamental disciplines as linear, vector algebras, image processing theory, and the basics of information theory were used. In general, the process of compressing hyperspectral aerospace images is carried out in several stages [14]:

- Determination of the correlation dependence of the brightness of various channels and creation of arrays of deviations of the calculated indicators from the actual ones;
- Formation of an auxiliary data structure based on the initial hyperspectral AI, storing unique paired groups of element values in byte representation, as well as address references to these unique paired groups;
- Compression of the data obtained after transformations by a standard entropy algorithm by processing the formed auxiliary data structures.

The first step is to calculate the deviation values of the linear dependence on the image variable matrix, which decomposes it into dimensions for each image

$$\mathbf{I}[m,n,k] = \begin{vmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} & \ldots \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{vmatrix}, \tag{1}$$

where m,n,k are the indices of rows, columns and channels of the original image; a_{11}, ..., a_{nn} – represents the value in bytes.

All values of the matrix (1) are recorded during the processing of the acquired images and then for statistical determination it is necessary to calculate the mathematical expectation for each channel separately:

$$\mathbf{M}[k] = \sum_{k=1}^{K} \mathbf{I}[m,n,k] \times \mathrm{p}_{\mathbf{I}}^{k}, \tag{2}$$

where k is the channel number, K is the number of channels, $\mathrm{p}_{\mathbf{I}}^{k}$ is the relative frequency of occurrence of the same byte size on channels.

Then, based on the obtained values and the formed matrices, the correlation coefficient is calculated, which has a standard notation in the form of:

$$\mathbf{R}[k] = \frac{\sum_{m,n} (\mathbf{I}[m,n,k] - \mathbf{M}[k])}{\left| \sum_{m,n} (\mathbf{I}[m,n,k] - \mathbf{M}[k]) \right|}. \tag{3}$$

It is worth noting that the correlation values are calculated for each channel separately and placed in an array. The resulting array allows you to determine the linear dependence by the formula

$$\mathbf{L}[k] = \mathbf{I}[m,n,k] \times \mathbf{R}[k] \tag{4}$$

The resulting linear dependence is then used to determine the deviation from the initial values according to the following dependence

$$\mathbf{I}'[m,n,k] = \begin{cases} \text{if } \mathbf{R}[k] > 0, \ \mathbf{I}[m,n,k]\text{-}\mathbf{L}[k\text{-}1] \\ \text{if } \mathbf{R}[k] \leq 0, \ \mathbf{I}[m,n,k] \end{cases} \quad \text{for} \quad m = 1..M, n = 1..N. \tag{5}$$

The obtained values are also recorded in this array. At the second stage, the obtained values are already carried out as a result, the obtained values are then applied in further transformations.

In the second step, an **array** $\mathbf{M}[j,k]$ is formed for each K channel, which contains unique paired size groups from the array $\mathbf{I'}[m,n,k]$. Figure 1 shows a structured diagram of the data flow and transformation processes

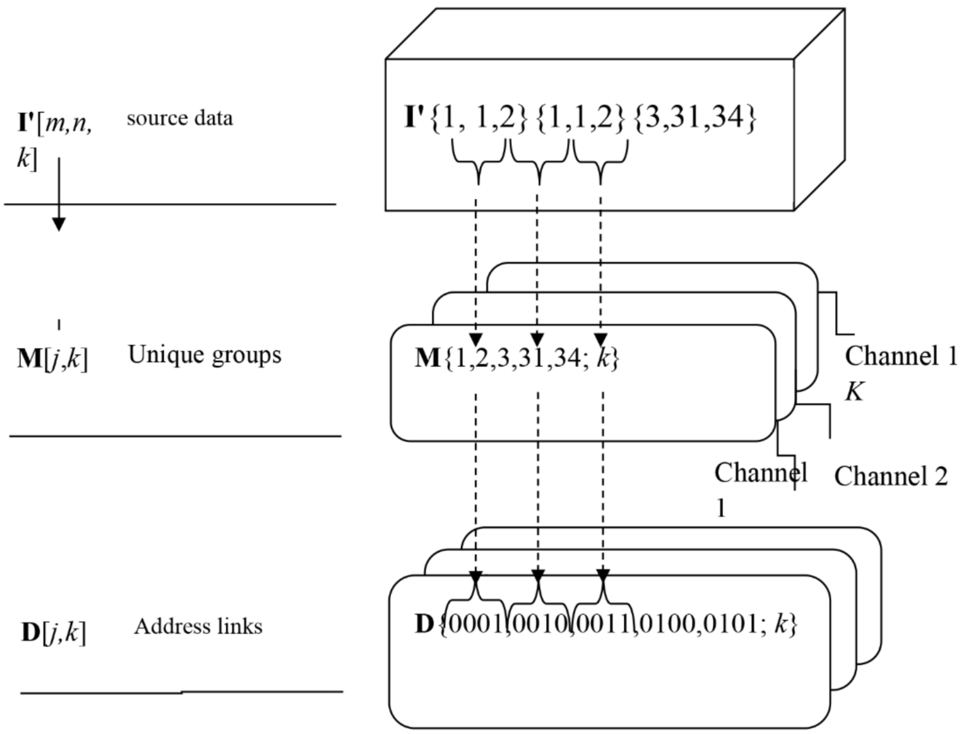

Figure 1. Procedure for forming an auxiliary data structure

Moreover, in the absence of repetitions, these values are entered into another array $J=(M\times N\times K)/2$, $k=1,2,..,K$. Hence the array $\mathbf{D}[j,k]$ is formed for address references to unique paired groups from $\mathbf{M}$[j,k].

Therefore, at the third stage, arithmic coding is used to transfer the archive $\mathbf{D}'[j,k]$ to the array. As a result, the array will be restored by arithmic decoding. In previous works devoted to this problem, a solution was proposed based on the Walsh-Hadamar transformation method, which is based on the use of the Hadamard transformation matrix [14]:

$$H_1 = \frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}. \tag{6}$$

Moreover, all subsequent transformation matrices are determined by the formula:

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

$$H_m = \frac{1}{\sqrt{2}} \begin{pmatrix} H_{m-1} & H_{m-1} \\ H_{m-1} & -H_{m-1} \end{pmatrix}. \tag{7}$$

These matrices will be needed in the future to improve the existing method. Fully the process can be demonstrated as the structural scheme below on the figure 2.

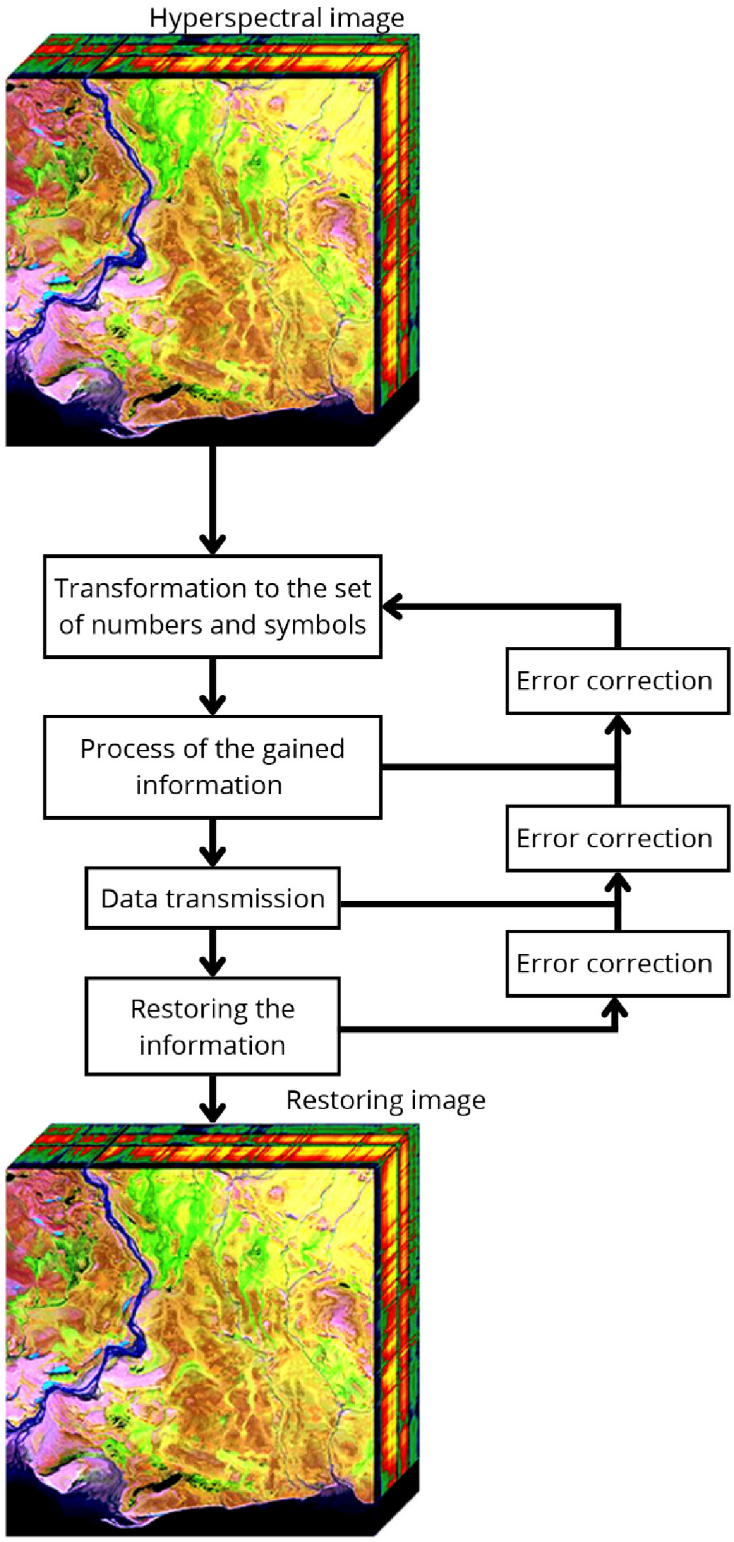

Figure 2. Structural scheme for the hyperspectral image processing

DOI: 10.37943/18BIAC9844

The process of the compression lies in two sections of the scheme, which are "Transformation to the set of numbers and symbols" and "Process of the gained information".

Results

In order to develop a lossless data compression algorithm in order to improve the efficiency of information storage and transmission. It should be noted that the method will take into account inter-band correlation and difference transformations, and will be characterized by a decrease in the range of initial values through the creation of groups of channels with a high intragroup correlation. As part of this approach, optimal parameters will be selected to ensure a high degree of compression while maintaining data quality.

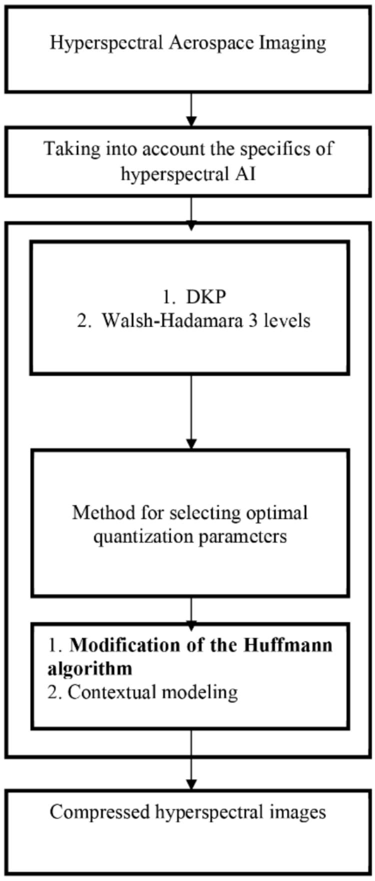

Figure 3. Diagram of the data flow and processes

The advantage of the original algorithm:

- the lossless compression algorithm taking into account inter-band correlation, regression analysis and a modified Huffman algorithm allows you to increase the compression ratio to (*D>6) than in the analogue of* JPEG *Lossless* and universal archivers;
- the proposed approach to finding the best groups of channels at a given correlation value increases the efficiency of using the stage of subtracting channels (difference transformation);
- the results of comparison of transformed hyperspectral AI allow us to assume the efficiency of using the stages of regression transformation and multi-threaded processing, which shows good results in calculating compression algorithms;

The computational efficiency disadvantage of the previous algorithms is eliminated by using a multithreaded processing step in the compression algorithm.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

Transformation of the data structure based on the initial hyperspectral AI storing the values of wavelet coefficients on the example of the one-dimensional Haar wavelet.

The main principle of wavelet analysis is the selection of information at different levels of detail. These levels of detail can be interpreted as scale or resolution settings. Wavelet analysis, which is used to compress images, is based on extracting the information contained in the details of the image and removing those details that have little impact on the overall perception of the image.

The system of Haar functions has key properties characteristic of wavelets: localization (limited carrier), orthogonality, normalization, and zero mean. Today, many researchers, especially those working in the field of practical applications for image compression, understand wavelets as a wider range of functions.

The functions proposed by the Hungarian mathematician A. Haar in 1910 and later called Haar wavelets are discrete and especially convenient for the initial analysis of images. The Haar function is defined by the following formula:

$$\Psi(t) = \begin{cases} 1 \text{ if } t \in [0, 1/2), \\ -1 \text{ if } t \in [1/2, 1), \\ 0, \text{ if } t \notin [0, 1) \end{cases}$$

Haar transform wavelet:

- The method of transformation is that the lines of the image are transformed, thereby a one-dimensional wavelet transformation is carried out.
- finding half-sums and half-differences using Haar wavelets, as the use of low-pass and high-frequency filters.

Let's consider the details of the stages of transforming the values of the hyperspectral AI channel $\mathbf{I}[m,n,k]$ *based on the one-dimensional Haar wavelet. Next steps:*

- A sequence is formed based on the original image with the following function:

$$f(I[m,n,k]) = \mathrm{I}[\mathrm{m}+1, \mathrm{n}+1, \mathrm{k}-1]_1 \times \phi_{n.0}(I[m,n,k]) + \ldots$$
$$\ldots + \mathrm{I}[\mathrm{m}+1, \mathrm{n}+1, \mathrm{k}-1]_{2^{\mathrm{n}}} \times \phi_{n,.2^{n-1}}(I[m,n,k]),$$

where n is the ordinal number of the addend.

- calculate the average values of pairs of adjacent values using the following formulas: half-sums

$$a_{\mathrm{I}[m,n,k-1]} = \frac{\mathrm{I}[m+1, n+1] + \mathrm{I}[m+2, n+2]}{2}$$

and semi-differences

$$d_{\mathrm{I}[m,n,k-1]} = \frac{\mathrm{I}[m+1, n+1] - \mathrm{I}[m+2, n+2]}{2}$$

- Obtaining new data structures of hyperspectral AI $a_{\mathrm{I}[m,n,k-1]}$ and $d_{\mathrm{I}[m,n,k-1]}$ based on half-sums and differences;
- decompose $f(\mathrm{t})$ based on step 2 and 3 making up the half-sum and half-difference:

$$f(\mathbf{I}[m,n,k]) = a_{\mathrm{I}[m,n,k-1],0} \times \varphi_{I[m,n,k-1],0}(I[m,n,k]) + \ldots$$
$$\ldots + a_{\mathrm{I}[m,n,k-1],2^{n-1}} \times \phi_{I[m,n,k-1],2^{n-1}-1}(I[m,n,k]) + d_{\mathrm{I}[m,n,k-1],0} \times \psi_{I[m,n,k-1],0}(I[m,n,k]) + \ldots$$
$$d_{\mathrm{I}[m,n,k-1],2^{n-1}-1} \times \psi_{I[m,n,k-1],2^{n-1}-1}(I[m,n,k]);$$

- Calculation of wavelet coefficients: low-frequency

$$a_{\mathrm{I}[m,n,k-1],n} = \frac{\mathrm{I}[m+1,n+1]_{n+1} + \mathrm{I}[m+2,n+2]_{n+2}}{\sqrt{2}},\ n = 0,\ldots 2^{n-1}-1;$$

using the properties of orthogonality and normalization of the function $f\,\mathbf{I}[m,n,k]$, Let's calculate the high-frequency coefficients $d_{\mathrm{I}[m,n,k-1]}$ according to the following formula:

$$d_{\mathrm{I}[m,n,k-1],j} = \frac{\mathrm{I}[m+1,n+1]_{j+1} - \mathrm{I}[m+2,n+2]_{j+2}}{\sqrt{2}},$$

где $j = 0,\ldots 2^{n-1} - 1$

The result will be placed in matrices $I^{\Psi}_{Haar\ I}[m,n,k]$.

After converting the Haar wavelet, we get the wavelet coefficients of two components – low-frequency and high-frequency. If it is necessary to compress this image, pay attention to the magnitude of the values of the high-frequency coefficients that can be subject to the quantization procedure. We remember only the given % of the highest coefficients (low-frequency), the remaining lowest (%) coefficients are assumed to be equal to zero (high-frequency).

At the stage of restoring the original channels of the image, the spectral components are decoded by transforming the matrix of the Haar wavelet coefficients.

As the result, the compression ratio for multistage process achieves the value of 5.5.

Discussion

In this study, it can be noted that it is necessary to pre-process images, namely, to determine the necessary information for further transmission. According to the review, most of the methods rely on the application of artificial intelligence for the most part, applying known methods. For example, such systems with CNN are currently popular, as indicated in [6] and [7]. Other methods are based on the use of EEA [11], [12].

Therefore, for pre-preparation, the Walsh-Hadaamar transform was proposed, the method of which is to apply a special matrix. This approach allows you to divide the hyperspectral cube of images into layers. Moreover, the proposed method will make it possible to divide images into spectra and determine the most useful images among all layers. It is worth noting that the standard algorithm has the same sequence as the one proposed in this paper. Considering this algorithm, it can be noted that the comparison of the main information in the matrix (1) allows you to solve this problem with the help of correction during image restoration. Restoration and accuracy is carried out using (3)-(5).

In the future, it is also worth noting that it is possible to solve these issues with the help of such devices as boards from NVIDIA, namely Jetson [8], on the other hand, it is also possible to use FPGA, which will simplify the process many times over [13]. The application of the NVIDIA Jetson or FPGA is very common in the unmanned aerial vehicle (UAV), for FPGA it is even used in satellites, therefore integration of the algorithm in the controllers of the vehicles makes it more effective.

Conclusion

An algorithm for lossless compression of byte processing has been developed, taking into account inter-band correlation and difference transformations, which is characterized by data transformation with a decrease in the range of values, initial values by forming a set of groups of channels, with a high intra-group correlation of the corresponding pairs, with the selection of optimal parameters. A method is proposed in the form of selecting channels by grouping and ordering them by selecting the best correlated channel. The advantage of using inter-channel correlation is to find the best (reference) channel that determines the sequence of the grouping compression algorithm.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 18, JUNE 2024

The advantage of conversion is the ability to identify low-frequency areas in the image while maintaining excellent quality, which increases the compression ratio.

Based on the proposed schemes and the developed effective algorithms for lossless hyperspectral AI compression, it can be concluded that the requirements for high compression ratio and computational efficiency have been met.

References

[1] Su, P., Liu, D., Li, X., & Liu, Z. (2018). A saliency-based band selection approach for hyperspectral imagery inspired by scale selection. IEEE Geoscience and Remote Sensing Letters, 15(4), 572-576. https://doi.org/10.1109/LGRS.2018.2800034

[2] Dou, Z., Gao, K., Zhang, X., Wang, H., & Han, L. (2021). Band selection of hyperspectral images using attention-based autoencoders. IEEE Geoscience and Remote Sensing Letters, 18(1), 147-151. https://doi.org/10.1109/LGRS.2020.2967815

[3] Feng, Y., Yuan, Y., & Lu, X. (2016). A non-negative low-rank representation for hyperspectral band selection. International Journal of Remote Sensing, 37(19), 4590-4609. https://doi.org/10.1080/01431161.2016.1214299

[4] Zhong, S., et al. (2019). Class feature weighted hyperspectral image classification. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(12), 4728-4745. https://doi.org/10.1109/JSTARS.2019.2950876

[5] Wang, C., Zhang, L., Wei, W., & Zhang, Y. (2020). Hyperspectral image classification with data augmentation and classifier fusion. IEEE Geoscience and Remote Sensing Letters, 17(8), 1420-1424. https://doi.org/10.1109/LGRS.2019.2945848

[6] Yu, C., Han, R., Song, M., Liu, C., & Chang, C.-I. (2022). Feedback attention-based dense CNN for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 60, 1-16, Article 5501916. https://doi.org/10.1109/TGRS.2021.3058549

[7] Paoletti, M. E., Haut, J. M., Fernandez-Beltran, R., Plaza, J., Plaza, A., Li, J., & Pla, F. (2018). Capsule networks for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 1, 1-16. https://doi.org/10.1109/tgrs.2018.2871782

[8] Haut, J. M., Bernabé, S., Paoletti, M. E., Fernandez-Beltran, R., Plaza, A., & Plaza, J. (2019). Low-high-power consumption architectures for deep-learning models applied to hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters, 16(5), 776-780. https://doi.org/10.1109/LGRS.2018.2881045

[9] Wei, W., Li, W., Zhang, L., Wang, C., Zhang, P., & Zhang, Y. (2019). Robust hyperspectral image domain adaptation with noisy labels. IEEE Geoscience and Remote Sensing Letters, 16(7), 1135-1139. https://doi.org/10.1109/LGRS.2018.2889800

[10] He, N., et al. (2019). Feature extraction with multiscale covariance maps for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 57(2), 755-769. https://doi.org/10.1109/TGRS.2018.2860464

[11] Erturk, A. (2015). Enhanced unmixing-based hyperspectral image denoising using spatial preprocessing. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(6), 2720-2727. https://doi.org/10.1109/jstars.2015.2439031

[12] Delgado, J., Martín, G., Plaza, J., Jiménez, L.I., & Plaza, A. (2016). Fast spatial preprocessing for spectral unmixing of hyperspectral data on graphics processing units. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9(2), 952-961. https://doi.org/10.1109/JSTARS.2015.2495128

[13] Kowkabi, F., & Keshavarz, A. (2019). Using spectral geodesic and spatial Euclidean weights of neighbourhood pixels for hyperspectral endmember extraction preprocessing. ISPRS Journal of Photogrammetry and Remote Sensing, 158, 201-218. https://doi.org/10.1016/j.isprsjprs.2019.1

[14] Sarinova, A., Dunayev, P., Bekbayeva, A., Mekhtiyev, A., & Sarsikeyev, Y. (2022). Development of compression algorithms for hyperspectral aerospace images based on discrete orthogonal transformations. Eastern-European Journal of Enterprise Technologies, 1(2), 22-30. https://doi.org/10.15587/1729-4061.2022.251404