Method of multilevel spectral processing of infrared images in bit planes

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Abstract

Improving the efficiency of remote thermal monitoring systems requires the development of image compression methods adapted to the semantic properties of infrared (IR) images. IR images typically have a wide dynamic range, often reaching 16 bits per pixel, which creates significant difficulties for real-time processing and transmission, especially in conditions of limited communication channel bandwidth. Traditional compression standards—such as JPEG, JPEG2000, and H.265—demonstrate low efficiency when working with IR data, mainly due to their failure to account for the specific spectral structure, bit-plane hierarchy, and local temperature variations. To address these limitations, this work proposes a compression method based on the decomposition of IR images into two components: the most significant and least significant bits, with subsequent differentiated processing of each layer. At the initial stage, the image is divided into 8×8 pixel segments, which, in turn, are divided into 4×4 mini-segments. Within each mini-segment, a transformation into a different space is performed, which forms a residual representation. These residual data are processed using a recursive one-dimensional Haar wavelet transform, which is performed until only one low-frequency coefficient remains. This approach ensures effective energy concentration and multilevel spectral decomposition. A group coding method is also proposed. In this method, each mini-segment is encoded using a single code value formed from the high frequencies. Meanwhile, all low-frequency components of the segment are aggregated and encoded separately. As a result, the information of each initial segment can be represented by only five coefficients. This enables a significant reduction in data volume without compromising critical temperature information, thereby preserving the semantic integrity of the scene. Due to its computational simplicity and real-time processing capability, the proposed method is particularly suitable for resource-constrained platforms, such as unmanned aerial vehicles and portable thermal imaging devices.

Keywords

infrared images, bit layers, Haar wavelet transform, group coding, image compression

1. Introduction

Improving the efficiency of remote thermal monitoring systems requires the development of image compression methods tailored to the semantic properties of infrared (IR) imagery. IR images typically have a high dynamic range, often reaching 16 bits per pixel, which poses significant challenges for real-time processing and transmission, especially under bandwidth-constrained communication channels [1, 2, 3]. Traditional compression standards such as JPEG, JPEG2000, and H.265 are known to perform poorly on IR data, primarily due to their inability to account for the specific spectral structure, bit-plane hierarchy, and localized thermal variations inherent to such imagery [4, 5]. To address these limitations,

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this work proposes a compression method based on decomposing IR images into two components: higher-order and lower-order bits, followed by differentiated processing of each layer [6, 7, 8, 9].

Initially, the image is divided into 8x8 pixel segments, which are further partitioned into 4x4 mini-segments [10, 11, 12, 13]. Within each mini-segment, a transformation into the residual domain is applied, creating a residual representation. These residual data are then processed using a recursive one-dimensional Haar wavelet transform, which is executed until only a single low-frequency coefficient remains [14, 15, 16, 17]. This approach ensures efficient energy compaction and multilevel spectral decomposition. A group coding method is also proposed. In this method, each mini-segment is encoded using a single code value derived from its high-frequency components. Meanwhile, all low-frequency components from the segment are aggregated and encoded separately [18, 19, 20]. As a result, the information of each initial segment can be represented by just five coefficients. This significantly reduces the data volume without losing critical thermal information, thereby preserving the semantic integrity of the scene [21, 22, 23, 24]. Thanks to its computational simplicity and suitability for real-time processing, the proposed method is particularly appropriate for resource-constrained platforms such as unmanned aerial vehicles and portable thermal imaging devices [25, 26, 27, 28]. The growing need for real-time object monitoring, especially in limited visibility conditions, drives the active implementation of infrared (IR) cameras in critical areas such as defense, security systems, remote surveillance, and search-and-rescue operations. IR imaging has an advantage over traditional optical visualization methods due to its ability to capture the thermal radiation of objects, ensuring independence from external lighting, smoke, fog, and other obscuring factors. This makes the IR information channel an indispensable data source for unmanned aerial systems operating in complex and crisis environments [29, 30, 31].

At the same time, the processing and transmission of IR images are associated with a number of challenges. Unlike conventional visual images, infrared frames typically have a bit depth of 12-16 bits per pixel, which significantly increases their bit volume. Transmitting such data in real-time, especially under the limited bandwidth of on-board or mobile telecommunication systems, is accompanied by delays. To reduce them, compression methods focused on eliminating psychovisual redundancy are used. However, such methods, aimed at human perception, do not take into account the thermal semantics of the images, which leads to the loss of critically important information and the appearance of distortions [32, 34, 33].

Standardized coding algorithms, particularly JPEG, JPEG2000, or H.265/HEVC, are not adapted to the specifics of infrared data. They do not account for the nature of thermal signatures and cause a loss of thermal integrity, which is key in many applied tasks. Furthermore, traditional compression methods do not consider the spectral heterogeneity and non-uniform distribution of information content among the bit-planes, which are characteristic of IR images. This significantly limits the potential for their effective use in tasks of thermal analysis, object detection, and identification. In this regard, there is a relevant scientific and applied problem to increase the efficiency of processing and transmitting IR images in remote surveillance and search systems by ensuring an enhanced level of data integrity and transmission speed.

2. Analysis and problem statement

Modern image compression methods, including JPEG, JPEG2000, H.264/AVC, and H.265/HEVC, are widely used to reduce the bit volume of digital images and video. These methods are based on the use of spatio-frequency transforms (e.g., DCT or DWT), subsequent quantization of coefficients, and entropy coding. The effectiveness of these standards is based on eliminating the psychovisual redundancy of information that is barely noticeable or insignificant to human visual perception. However, these technologies are primarily oriented towards visual (RGB) images and do not consider the specifics of infrared (IR) data.

In the case of IR images, especially those with an extended dynamic range, the preservation of thermal semantics—that is, the precise value of the objects' thermal signatures—is key. For such images, even a slight change in pixel values can lead to the loss of important information about the physical state of the scene. Consequently, traditional compression methods can cause distortions of the temperature profile, which is critical for detection, identification, and decision-making tasks in security and defense systems.

Furthermore, IR images have a number of statistical features that are poorly handled by classical algorithms. First, the bit-planes of an IR frame exhibit a non-uniform distribution of information: the most significant bits correspond to global structures and object contours, while the least significant bits relate to fine details or noise. Second, in the spectral domain, IR images are characterized by a non-uniform energy distribution, depending on the local characteristics of the scene's thermal field. None of the above properties are utilized in typical coding standards.

A promising approach is one that combines the advantages of spectral image representation with group coding of bit layers, which allows not only for adaptation to the local features of the frame but also for minimizing structural redundancy without losing important thermal information. Therefore, the purpose of this article is to develop a method for spectral-group coding of bit layers of infrared images.

3. Development of the method of spectral-group coding of bit layers of infrared images

Infrared images formed by thermal imaging cameras can have a bit depth of 16 bits per pixel. This leads to a significant increase in data volume. Most traditional coding algorithms are not adapted to such a depth, which limits their effectiveness both in terms of compression and the preservation of information content. In particular, failing to account for the bit structure leads to uniform compression of all components, although their significance differs substantially.

In this context, it is advisable to represent the initial 16-bit IR image as two separate components: a most significant bit (MSB) layer and a least significant bit (LSB) layer. Such a decomposition allows for the differentiated processing of data depending on their significance. The MSB layer carries the key semantics of the image—its structure, object shapes, boundaries, and other macroscopic characteristics. The LSB layer, conversely, reflects subtle temperature fluctuations, high-frequency details, or thermal noise. This allows for the application of more aggressive compression to the less informative layers without losing thermal accuracy.

Let there be an infrared image $A \in \mathbb{N}^{H\times W}$, where each pixel value is $A_{x,y} \in \left[0, 2^{16}-1\right]$. The value of each pixel can be decomposed as:

$$A_{x,y} = \sum_{m=0}^{15} b_m(x,y) \cdot 2^m, \tag{1}$$

where $b_m(x,y) \in \{0,1\}$ - is the value of the m-th bit of the pixel at position (x, y). Next, we introduce a threshold index $t \in \{1,\dots,15\}$, that separates the most significant and least significant bits. For example, for $t = 8$, two components are formed:

- most significant bit layer: $A_H(x,y) = \sum_{m=t}^{15} b_m(x,y) \cdot 2^m$;
- least significant bit layer: $A_L(x,y) = \sum_{m=0}^{t-1} b_m(x,y) \cdot 2^m$.

Thus, from one 16-bit image, two images, A_H and A_L of the same size $H \times W$ are formed, which have different informational natures. The image A_H is responsible for reproducing the macroscopic structure of the scene, including contours, shapes, and thermal anomalies — elements that are of key importance for object identification. In turn, the image A_L is characterized by greater variability, contains high-frequency components and micro-fluctuations of temperatures, which can be used to improve detail or as a source of entropy reserve during compression.

To ensure adaptive local analysis of the infrared image during the spectral-group coding process, a preliminary spatial-structural segmentation is applied. It allows for the localization of processing within small areas of the image, which significantly increases the efficiency of subsequent spectral analysis, reduces structural redundancy, and allows for the adaptation of the compression level to the local level of information content. At the first stage of segmentation, the image A is divided into non-overlapping blocks of a fixed size of 8×8 , which are subsequently considered as segments. The number of segments vertically and horizontally is determined by the ratios:

$$N_v = \left\lfloor \frac{H}{8} \right\rfloor, \quad N_h = \left\lfloor \frac{W}{8} \right\rfloor, \tag{2}$$

where N_v — the number of segments vertically, N_h — horizontally. The total number of segments in the image is:

$$N_{\text{seg}} = N_v \cdot N_h. \tag{3}$$

The segment located at coordinates (x, y), where $1 \leq x \leq N_v$, $1 \leq y \leq N_h$, is referred to as:

$$S_{x,y} \in \mathbb{N}^{8\times 8}. \tag{4}$$

Each segment $S_{x,y}$ is then subjected to a detailed breakdown—mini-segmentation—which allows for the identification of intra-segment non-uniformities. Specifically, the segment $S_{x,y}$ is divided into four non-overlapping mini-segments of size 4×4 pixels, denoted as - $S_{x,y}^{(m)} \in \mathbb{N}^{4\times 4}$, where $m \in \{1, 2, 3, 4\}$ corresponds to the position:

- $S_{x,y}^{(1)}$ - upper left minisegment;
- $S_{x,y}^{(2)}$ - upper right minisegment;
- $S_{x,y}^{(3)}$ - lower left minisegment;
- $S_{x,y}^{(4)}$ - lower right minisegment.

That is, minisegments $S_{x,y}^{(m)}$ have the following spatial representation:

$$S_{x,y} = \begin{bmatrix} S_{x,y}^{(1)} & S_{x,y}^{(2)} \\ S_{x,y}^{(3)} & S_{x,y}^{(4)} \end{bmatrix} \tag{5}$$

To apply the described segmentation scheme to the formed bit layers S_H and S_L we introduce the following notation system:

- $A_H S_{x,y}$ - segment of the most significant bit-plane;
- $A_H S_{x,y}^{(m)}$ - mini-segment of the most significant bit-plane;
- $A_L S_{x,y}$ - segment of the least significant bit-plane;
- $A_L S_{x,y}^{(m)}$ - mini-segment of the least significant bit-plane.

Within the framework of constructing an effective method for compressing infrared images, the preliminary transformation of local blocks into a form that enhances the detection of structural patterns and helps reduce entropy plays a special role. One such approach is to convert each local mini-segment into a different space. The purpose of this transformation is to eliminate the local constant component of the signal (background level) and to reduce the mean value and variation of the block elements, which directly contributes to increasing the efficiency of spectral analysis and subsequent compression.

Let the pixel values in a mini-segment $S_{x,y}^{(m)}$ be denoted as $S_{x,y}^{(m)}(i,j)$, where $i, j \in \{1, 2, 3, 4\}$. For each mini-segment, its minimum value is determined:

$$\mu_{x,y}^{(m)} = \min \left\{ S_{x,y}^{(m)} \right\}. \tag{6}$$

Next, this minimum value is subtracted from each element of the mini-segment $S_{x,y}^{(m)}$ necessary to subtract the specified minimum value $\mu_{x,y}^{(m)}$:

$$\Delta S_{x,y}^{(m)}(i,j) = S_{x,y}^{(m)}(i,j) - \mu_{x,y}^{(m)}, \quad \forall i, j. \tag{7}$$

That is, the difference between any two elements of a mini segment remains unchanged:

$$\Delta S_{x,y}^{(m)}(i,j) - \Delta S_{x,y}^{(m)}(p,q) = S_{x,y}^{(m)}(i,j) - S_{x,y}^{(m)}(p,q), \tag{8}$$

which means preserving local gradients and structural characteristics of the image.

As the result represents local deviations relative to the minimum value, the transformation into the difference space serves to remove the DC component, which carries no useful structural information but significantly affects the signal's amplitude.

An additional advantage is the reduction of the value range within the mini-segment, which is defined as:

$$\mathrm{range}(\Delta S_{x,y}^{(m)}) = \max(S_{x,y}^{(m)}) - \min(S_{x,y}^{(m)}). \tag{9}$$

This reduction in range leads to a decrease in variance and mean, which in turn lowers the block's entropy, improves the efficiency of the spectral transform, and reduces the volume of encoded information. This is especially important in infrared images, where the temperature of the scene varies slightly, but the relative gradients between neighboring pixels carry important semantic information.

By applying a difference transform to the minisegments of bit layers A_H and A_L we obtain the following notations:

- $A_H \Delta S_{x,y}^{(m)}$ - difference minisegment of the upper bit layer A_H ;
- $A_H S_{x,y}^{(m)}$ - $A_L \Delta S_{x,y}^{(m)}$ - difference minisegment of the lower bit layer A_L .

After converting the mini-segments into the difference space, it is advisable to perform a spectral transformation, which allows the representation of local temperature gradients in the frequency domain. Among possible spectral approaches, such as DCT (Discrete Cosine Transform) or DFT (Discrete Fourier Transform), the use of the discrete wavelet transform based on the Haar basis is proposed. It has the following advantages:

- computational simplicity - the algorithm has low computational complexity as it is implemented through simple additions, subtractions, and divisions, which is critical for implementation on embedded systems or platforms with limited computational resources;
- frequency decomposition - after the wavelet transform, most of the energy is localized in the low-frequency coefficient, while the high-frequency coefficients tend to have small values, which opens up the possibility of adaptive, aggressive compression.

Consider the mini-segment $\Delta S_{x,y}^{(m)}$ as a one-dimensional vector:

$$\mathbf{v}^{(0)} = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_{16}\} \in \mathbb{N}^{1\times 16} \tag{10}$$

At the first step, pairs of adjacent elements are convolved to construct:

- approximation coefficients: $\mathbf{a}_k^{(1)} = \frac{\mathbf{v}_{2k-1}^{(0)} + \mathbf{v}_{2k}^{(0)}}{2}, \quad k = \{1, \ldots, 8\}$;
- detail coefficients: $\mathbf{d}_k^{(1)} = \frac{\mathbf{v}_{2k-1}^{(0)} - \mathbf{v}_{2k}^{(0)}}{2}, \quad k = \{1, \ldots, 8\}$.

Thus, we obtain two vectors:

- $\mathbf{a}^{(1)} \in \mathbb{R}^8$ - low-frequency coefficients;
- $\mathbf{d}^{(1)} \in \mathbb{R}^8$ - high-frequency coefficients.

The next step is to recursively apply the same procedure only to the low-frequency vector $\mathbf{a}^{(1)}$:

$$\mathbf{a}_k^{(2)} = \frac{\mathbf{a}_{2k-1}^{(1)} + \mathbf{a}_{2k}^{(1)}}{2}, \quad k = \{1, \ldots, 4\}; \tag{11}$$

$$\mathbf{d}_k^{(2)} = \frac{\mathbf{a}_{2k-1}^{(1)} - \mathbf{a}_{2k}^{(1)}}{2}, \quad k = \{1, \ldots, 4\}. \tag{12}$$

Then to:

$$\mathbf{a}_k^{(3)} = \frac{\mathbf{a}_{2k-1}^{(2)} + \mathbf{a}_{2k}^{(2)}}{2}, \quad k = \{1, 2\}; \tag{13}$$

$$\mathbf{d}_k^{(3)} = \frac{\mathbf{a}_{2k-1}^{(2)} - \mathbf{a}_{2k}^{(2)}}{2}, \quad k = \{1, 2\}. \tag{14}$$

Until only one low-frequency coefficient remains:

$$\mathbf{a}_1^{(4)} = \frac{\mathbf{a}_1^{(3)} + \mathbf{a}_2^{(3)}}{2}; \tag{15}$$

$$\mathbf{d}_1^{(4)} = \frac{\mathbf{a}_1^{(3)} - \mathbf{a}_2^{(3)}}{2}. \tag{16}$$

As a result of the recursive wavelet transform, we have:

$$\mathbf{W}(x) = \left\{\mathbf{a}_1^{(4)}, \mathbf{d}_1^{(4)}, \mathbf{d}_1^{(3)}, \mathbf{d}_2^{(3)}, \mathbf{d}_1^{(2)}, \mathbf{d}_2^{(2)}, \ldots, \mathbf{d}_4^{(2)}, \mathbf{d}_1^{(1)}, \ldots, \mathbf{d}_8^{(1)}\right\} \in \mathbb{R}^{1\times 16}. \tag{17}$$

where:

- $\mathbf{a}_1^{(4)}$ - is the single remaining low-frequency coefficient;
- all $\mathbf{d}_k^{(\ell)}$ - are high-frequency coefficients $\ell \in \{1, 2, 3, 4\}$, ordered by level of frequency detail (from coarse to fine) .

The described transformation into spectral space must be applied to the difference minisegments from the upper bit layer and the lower bit layer:

$$\mathbf{W}(\mathbf{I}_H \Delta S_{i,j}^{(k)}); \mathbf{W}(\mathbf{I}_L \Delta S_{i,j}^{(k)}). \tag{18}$$

To reduce the bit volume of the generated spectral coefficients they must be encoded using group coding:

$$x_{\text{gc}} = \text{GroupC}\left(\{x_1, \ldots, x_n\}\right); \tag{19}$$

where:

- $\{\mathbf{x}_1, \ldots, \mathbf{x}_n\}$ - set of values to be encoded;
- $\mathbf{x}_{\text{gc}}$ - generated code value.

For each mini-segment $S_{x,y}^{(m)}$ we will form a vector of high-frequency coefficients:

$$\mathbf{d}_{x,y}^{(m)} = \left(\mathbf{d}_1^{(4)}, \mathbf{d}_1^{(3)}, \mathbf{d}_2^{(3)}, \mathbf{d}_1^{(2)}, \ldots, \mathbf{d}_4^{(2)}, \mathbf{d}_1^{(1)}, \ldots, \mathbf{d}_8^{(1)}\right) \in \mathbb{R}^{15}. \tag{20}$$

Apply group coding to $\mathbf{d}_{x,y}^{(m)}$:

$$\text{GroupC}_{x,y}^{(m)} = \text{GroupC}(\mathbf{d}_{x,y}^{(m)}) \tag{21}$$

For each mini-segment $S_{x,y}^{(m)}$ a vector of high-frequency coefficients is formed and group coded into a single value $\text{GroupC}_{x,y}^{(m)}$. Since an $S_{x,y} \in \mathbb{N}^{8\times 8}$ segment consists of four mini-segments, it will have four high-frequency group codes $\mathbf{S}_{x,y}^{(m)}$ at $m = \{1, \ldots, 4\}$, then it will have 4 high-frequency group codes, one for each minisegment:

$$\left(\text{Group}\, C_{x,y}^{(1)},\ \text{Group}\, C_{x,y}^{(2)},\ \text{Group}\, C_{x,y}^{(3)},\ \text{Group}\, C_{x,y}^{(4)}\right). \tag{22}$$

Thus, instead of operating with 64 pixel values or 64 spectral coefficients, all information is compressed into 5 scalar codes, achieving a significant reduction in data volume.

By applying group coding to the spectral coefficients formed from the upper bit layer A_H and the lower bit layer A_L , separate code values will be formed for each bit layer:

- upper bit layer segment group codes $\mathbf{A}_H\,\mathbf{S}_{x,y}$:

$$A_H\,\text{Group}\,C_{x,y}=\left\{A_H\,\text{Group}\,C^{(1)}_{x,y},\;A_H\,\text{Group}\,C^{(2)}_{x,y},\;A_H\,\text{Group}\,C^{(3)}_{x,y},\;A_H\,\text{Group}\,C^{(4)}_{x,y}\right\};\quad(23)$$

- upper bit layer segment group codes $\mathbf{A}_L\,\mathbf{S}_{x,y}$:

$$A_L\,\text{Group}\,C_{x,y}=\left\{A_L\,\text{Group}\,C^{(1)}_{x,y},\;A_L\,\text{Group}\,C^{(2)}_{x,y},\;A_L\,\text{Group}\,C^{(3)}_{x,y},\;A_L\,\text{Group}\,C^{(4)}_{x,y}\right\}.\quad(24)$$

4. Conclusions

1. An approach to compressing infrared images based on spectral-group processing of bit layers has been substantiated. The proposed representation of 16-bit IR images in the form of most significant and least significant bit layers allows for consideration of the specific distribution of information in the bit structure and adaptation of processing methods to the semantic load of each layer. The expediency of separating structurally significant components at the bit-plane level has been demonstrated.

2. A procedure for multilevel segmentation has been developed and formalized, involving the division of the image into 8×8 segments and 4×4 mini-segments. This approach allows for the localization of analysis, adaptation to spatial heterogeneity, and reduction of statistical redundancy within each block.

3. A method for transforming mini-segments into a different space through local alignment relative to the minimum value has been proposed. This transformation eliminates the DC component, reduces entropy, and increases the efficiency of subsequent spectral processing while preserving local temperature gradients.

4. A multilevel one-dimensional Haar wavelet transform for processing mini-segments in a linear representation has been developed. A recursive implementation of the transform is proposed until one low-frequency and 15 high-frequency coefficients remain. This approach allows for frequency decomposition while preserving the order of components and promoting energy concentration in the approximation.

5. A functional model of group coding has been proposed, which involves compressing the spectral coefficients of each mini-segment into a single code value. The high-frequency coefficients of each mini-segment are processed separately, while the low-frequency coefficients of all mini-segments within a segment are processed jointly. As a result, each segment is represented by five group codes, which provide a high degree of compression while preserving the thermal structure of the scene.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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