Wavelet Coding of Off-axis Holographic Images

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ABSTRACT

Significant research efforts have been invested in attempting to reliably capture and visualize holograms since their inception in 1962. However, less attention has been given to the efficient digital representation of the recorded holograms, which differ considerably from digitally recorded photographs. This paper examines the properties of recorded off-axis holograms and attempts to find a suitable sparse representation for holographic data. Results show significantly improved Bjøntegaard delta PSNR up to 5 dB on average within a bit-rate range of 0.125 to 2 bpp when combining the direction-adaptive discrete wavelet transform with non-standard decomposition schemes for microscopic off-axis holographic recordings; up to 7.5% reduction of file size has been achieved in the lossless case.

Keywords: Holography, off-axis holography, wavelets, direction-adaptive discrete wavelet transform, packet decompositions, image compression, JPEG 2000

1. INTRODUCTION

3D visualization has gained popularity over the years, not only for the purpose of entertainment, but in many other fields such as medical imaging, microscopy, interferometry, and others. A significant part of the current publicly available 3D technology and content is based on stereoscopy: using a separate image (or video stream) for each eye. This technology has its limitations: no actual depth information is encoded and no parallax is present. Multiview displays can partially support (horizontal) half-parallax, but still they do not succeed fully in generating a smooth 3D rendering.

We perceive our surroundings as three-dimensional not only because of different information being fed to each of our eyes, but also because we capture the entire wavefront of light reflected on objects, which contains both amplitude and phase information. Classical photography does not allow this: the image is focused on a particular depth, retaining only the intensity information contained by the wavefront. For that reason, holography becomes a very valuable tool for image visualization; this is albeit not its only application: interferometry, non-destructive testing, data encoding, and certification are but a few examples [1].

Holography enables the full reconstruction of the wavefront of a scene. Traditional optical holography achieves this by means of recording sub-micron features of the scene’s wavefront with a light-sensitive medium. A CCD chip, paving the path for digital holography, can nowadays replace the analog medium.

Much like in photography, there are many benefits to the transition from analog to digital holography: it greatly facilitates the storage, transmission and analysis of the holograms and allows for the generation of artificial holograms. The latter will be crucial for future holographic applications.

Although significant progress has been made in the development of digital holography [2], we are not yet able to faithfully reproduce the wavefront of a scene. The three main challenges posed are related to:

- **Optical technology**: regular screens have typical pixel spacings of 100μm, but holographic displays require sub-micron pixel sizes [3].
- **Bandwidth**: full-fledged holographic screens will have to display images with both horizontal and vertical parallax, necessitating extreme resolutions. The bandwidth required for displaying these high-resolution images is huge.

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Computational processing these vast amounts of data is challenging; this is especially the case for rendering computer graphics based holography (CGH): the wavefront will have to be calculated for all possible viewing angles using complex diffraction models for light propagation.

The focus of this paper is to compress digitally recorded holograms to reduce bandwidth and storage requirements. The encoding of digitally recorded holograms differs significantly from regular images: off-axis holograms contain more high-frequency components and depict strong anisotropy (i.e., their properties differ depending on the direction).

Although the problem of compressing holographic data has been addressed before [4][5], most of the work has ignored the current state-of-the-art in image compression. Therefore, this paper will investigate the usage of a JPEG 2000 encoder architecture as a basis for the compression of holographic data and assessing the impact of deploying packet-based wavelet transforms and directional filter kernels.

2. HOLOGRAPHY

2.1 Capturing Holograms

Many methods with varying degrees of quality and feasibility exist for recording holograms [1]. The deployed setups contain generally the same key elements: in a generic setup, monochromatic coherent laser light is sent first through a beam-expander, which widens and further collimates the laser beam, ensuring that the object will be illuminated properly. Next, the expanded laser beam is split into two parts by a beam splitter: (1) a reference beam that will remain intact and that will serve as a carrier wave and (2) an object beam that will illuminate the object thereby containing the required object information.† These two beams will be recombined onto some recording material, which will capture the interference pattern generated by the two superposed beams. This recording material was classically a light-sensitive film (which can be developed much like photographic film) in analog holography, while for digital holography a CCD chip is being deployed.

The recording device will measure the irradiance $I$ of the interferogram, being the sum of both the reference beam $R$ and the object beam $O$ (with $\ast$ being the complex conjugate operator):

$$I = R + O = |R|^2 + |O|^2 + R^\ast \cdot O + R \cdot O^\ast$$

In order to reproduce the hologram, we can use the same reference beam again to illuminate the recorded hologram irradiance, which gives [6]:

$$\Psi = R \cdot I = R \cdot (|R|^2 + |O|^2) + |R|^2 \cdot O + R^2 \cdot O^\ast$$

The first term of the resulting equation produces zero-order diffraction, the second term will produce the real image and the third term will produce a twin image.

These terms will overlap and significantly degrade the real image to be viewed. In order to separate these terms, we can use off-axis holography: this is a capturing method using an angle between the reference and object beams in the setup instead of parallel beams. That way, the three terms will be reconstructed at different locations in the reconstruction plane when using off-axis holographic captures (Figure 2), which will allow the viewer to set the focus on the real image; that way, the undesirable terms will be barely visible (or even evanescent).

The off-axis holographic configuration is often used in digital holographic microscopy (DHM) for example for the analysis of biological samples [6] and materials, characterization of lenses [7], and tomography.

Five different off-axis holographic test images are used in this paper (data courtesy of Lyncée Tec SA):

- Neuron: a slice of neuronal tissue; 1024x1024 pixels, 8 bpp (transmission imaging)
- Erythrocyte: erythrocytes from a blood sample; 512x512 pixels, 8 bpp (transmission imaging)
- Microlenses: a hologram from an array of microlenses; 1024x1024 pixels, 8 bpp (transmission imaging)
- Ball: the surface of a metallic micro-ball; 1024x1024 pixels, 8 bpp (reflection imaging)
- Scratch: a scratch in brittle material; 1024x1024 pixels, 8 bpp (reflection imaging)

† Sometimes, the laser beam is being split before it gets expanded for practical reasons, as shown in Figure 1.
These holograms can be recorded by either using transmission or reflection imaging, depending on the nature of the specimen (e.g. biological cells will be recorded by using transmission holography due to their transparency). The schematic of a transmission holographic microscope is shown on Figure 1 as an illustration [6].

![Figure 1: Schematic of the setup for holographic microscope for transmission imaging](image1)

Figure 2: Off-axis hologram reconstruction on observation plane $\Psi$ with reconstruction distance $d$.

3. JPEG 2000

To encode the digital holographic data we will utilize the JPEG 2000 image coding framework [8]. The JPEG 2000 standard is the successor of the well-known and widely used JPEG standard. This codec is well-suited for the targeted application domain because of its (1) modular and extendable architecture and (2) excellent rate-distortion behavior. It supports both lossy and lossless compression. Lossy compression reduces the image fidelity to improve the compression rate while ultimately lossless compression allows for the exact reconstruction of the original image. Moreover, lossy-to-lossless compression functionality is facilitated.

3.1 JPEG 2000 Architecture

JPEG 2000 has a modular architecture that consists out of the following core modules: image tiling, a wavelet transform, embedded encoding of code-blocks and finally a rate-distortion optimization mechanism [8]. The tiling component will
not be utilized in the presented research and is actually seldom used, except in cases where the images are too large to be processed by one wavelet transform module because of memory constraints. Next, the tile samples are wavelet transformed, which results in a wavelet domain representation of the image (or each tile), decomposed into different frequency subbands. These subbands are further split into smaller code-block units and each of these code-blocks is separately entropy encoded. Embedded code-block coding employs fractional bit-plane scanning and context-based adaptive arithmetic coding to generate independent embedded bit-streams per code-block. Afterwards, the rate-distortion optimizer combines these bit-streams such that based on the requested functionality and rate vs. quality requirements, optimal rate-distortion coding performance is delivered for the produced JPEG 2000 code-stream. As such, low-frequency components (corresponding to general image features) will be found at the beginning of the code-stream, allowing users to see a low-resolution version of the image right away when progressively decoding an image. The combination of low-level block encoding with rate-distortion optimization is known as Embedded Block Coding by Optimized Truncation (EBCOT) [9].

![Diagram of JPEG 2000 architecture](image)

**Figure 3:** Schematic of the JPEG 2000 architecture

### 3.2 Discrete Wavelet Transform

A one-dimensional Discrete Wavelet Transform (DWT) can essentially be summarized as successively applying a pair of lowpass and highpass filters on the image, both followed by a dyadic downsampling. To obtain a multiresolution decomposition – in a classical setting – the low frequency subband is further decomposed. Many different wavelet filters can be used. Some of them have the “perfect reconstruction” property (e.g. Haar, 5/3), meaning that in the absence of quantization errors, perfect image reconstruction is possible from the resulting wavelet coefficient; these filters often do have integer taps. However, floating-point taps typically result in higher compression efficiencies [10] such as the well-known Daubechies 9/7 filter bank.

The 1D-DWT can be readily extended to a two-dimensional transform, by applying the filters twice: once along the columns and once along the resulting rows. Consequently, one decomposition leads to four subbands, respectively named LL, HL, LH, HH; these indicate whether it is a lowpass (L) or highpass (H) filtered signal, respectively in the x- and y-directions. In addition, subbands are identified by a number prefix indicating the wavelet decomposition level.

Due to the general properties of natural images, adjacent pixels will be highly inter-correlated in their intensities. This translates to a very non-uniform power distribution, with most of the energy confined to the lower frequency subbands. More specifically, research has shown [12] that the power spectrum distributions of natural images have a $1/f^2$ shape (with $f$ being the spatial frequency).

Given those characteristics, applying the Mallat wavelet decomposition [11] will result in a sparse wavelet coefficient distribution in the highpass subbands, which is beneficial for compression. However, holographic recordings have different properties than natural images; these recordings have different power spectrum distributions and are often not
isotropic. The first characteristic can be addressed by deviating from the classical Mallat decomposition and devising a packet-based decomposition that allow for the decomposition of the high-frequency subbands as well (see Figure 4). The latter characteristic calls for directional wavelet filters that will be addressed in the next section.

![Figure 4: Diagrams of tested decompositions using 3 levels, in reading order: Mallat, Pack1, Pack2, and Full Packet. Darker squares correspond to channels with more energy per coefficient.](image)

### 3.3 Directional Wavelets

A classical 2D-wavelet transform can be viewed as a tensor product of the 1D transform in the horizontal and vertical directions. Nonetheless, as indicated earlier, these do not fully utilize the potential of capturing directionality in a picture when that directionality is not aligned with the x- or y-axis.

As a solution, one could use many of the available filters with inherent directionality (such as the Gabor filter e.g.). Unlike classic wavelets though, these filters are not separable; they cannot be represented as a tensor product of 1D transforms. Directional wavelets on the other hand are both oriented and separable. The Direction-Adaptive Discrete Wavelet Transform (DADWT) as proposed in [13] is a DWT with modified pixel sampling operations that are adapted to the local geometry of the image.

Performing the DWT along different directions has some restrictions however:

- We are confined to a discrete grid, which limits the possible transform directions. One could take the sampling steps to be arbitrarily large to approximate any wanted direction. However, this is not recommended as the correlation between sampled pixels reduces with the relative distance up to a point where no correlation is present between them; this will be detrimental for the compression performance.
- The downsampling step has to be taken into account. It is not possible to use coefficients that will be omitted during the downsampling, in order to preserve causality (and to facilitate the inverse transform). We therefore have to restrict sampling to even (or odd) columns (or rows, depending on the current sample and transform direction).
In essence, the image is split into small evenly sized blocks on which multiple direction-adaptive transforms are applied. Some directions will locally perform differently than others depending on the inherent directionality of the block. The best performing vector directions on each block will be kept. This will require additional information to be encoded [14] (the index of every applied transform on the image), but this will be compensated for if the image contains enough directional features, which is often the case.

Naive applications of this algorithm will require an exhaustive search for every proposed direction within every block. This can be sped up, as shown in [15].

4. EXPERIMENTS AND ANALYSIS

4.1 Performance Analysis

The experiments were conducted on the five off-axis holographic captures, as well as a few publicly available natural images as reference (“Lena”, “Barbara” and “Mandrill”). All the images have a bit-depth of 8 bit, with resolutions of either 512x512 or 1024x1024 pixels.

In pursuance of characterizing the performance of a regular wavelet transform decomposition on holographic recordings, the performance of both lossless (5/3 kernel, in bits-per-pixel) and lossy (9/7 kernel, in PSNR) for multiple bit-rates are shown on the table below, compared to natural images. The Peak Signal-to-Noise Ratio* (PSNR) quantifies the distortion introduced by the compression system. It is calculated as follows:

\[
PSNR = 10 \cdot \log \left( \frac{A_{max}^2}{MSE} \right) \quad \text{with} \quad MSE = \frac{1}{n} \sum_{i=1}^{n} (A_i - B_i)^2
\]

where \( A \) is the original image, \( A_{max} \) its maximum pixel value (in casu 255), \( B \) the reconstructed image and \( n \) the number of pixels in the image.

These results indicate that regular wavelets already perform reasonably well for off-axis holographic recordings. There is however still potential for further improvement, due to the particular properties of holographic captures, as will be shown in the following section.

<table>
<thead>
<tr>
<th></th>
<th>Lena</th>
<th>Barbara</th>
<th>Mandrill</th>
<th>Neuron</th>
<th>Erythocyte</th>
<th>Microlenses</th>
<th>Ball</th>
<th>Scratch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lossless (bpp)</td>
<td>4.35</td>
<td>4.81</td>
<td>6.14</td>
<td>4.67</td>
<td>4.91</td>
<td>4.12</td>
<td>5.67</td>
<td>4.44</td>
</tr>
<tr>
<td>2 bpp (dB)</td>
<td>44.76</td>
<td>43.05</td>
<td>34.61</td>
<td>43.47</td>
<td>42.89</td>
<td>47.07</td>
<td>36.81</td>
<td>43.74</td>
</tr>
<tr>
<td>1 bpp (dB)</td>
<td>40.23</td>
<td>37.08</td>
<td>28.97</td>
<td>37.62</td>
<td>37.49</td>
<td>41.11</td>
<td>29.50</td>
<td>38.05</td>
</tr>
<tr>
<td>0.5 bpp (dB)</td>
<td>37.07</td>
<td>32.07</td>
<td>25.44</td>
<td>33.36</td>
<td>29.93</td>
<td>35.06</td>
<td>25.24</td>
<td>35.76</td>
</tr>
</tbody>
</table>

4.2 Interpreting the data

Off-axis holographic recordings differ from natural images in several ways. Salient features in these recordings are the fringes, which are fairly regular and strongly oriented. The Fourier transform exhibits an additional peak centred at some specific high frequency and orientation (Figure 5); this contrasts with the singular peak in the middle according to the
$1/f^2$ power spectrum distribution [12]. The additional peaks in the holographic recordings do in fact correspond to the encoded information of the real image and the twin image [16].

![Figure 5: Holographic Capture of a scratch in brittle material (left), with its Fourier transform (right). The fringes can be seen in the zoomed-in part of the recording.](image)

We use a technique called “Independent Component Analysis” (ICA) to formally characterize the information content of the data. This computational method will analyse the image (or any multivariate signal) into statistically independent additive components, by searching for “natural” axes that will minimize the mutual information by maximizing the non-Gaussianity. These components then indicate where most of the information content is localized.

The ICA method used in this paper is based on [17]: “topographic ICA”. This is a generative model combining topographic mapping with regular ICA, using a distance metric defined as the mutual information implied by the higher-order correlations, which gives the natural distance measure in the context of ICA. The resulting components resemble the behaviour of complex cells (found in the visual cortex) in their responses, which is indicative of the applicability of this method to imagery.

In this experiment, individual components have dimensions of 16x16 pixels. The independent components of natural images are mostly constituted of edges in every possible orientation (Figure 7). The visually most interesting information tends to lie in the edges: these correspond to high-frequency information. The ICA components of the holographic captures appear to be very different: most of the generated basis functions are slight variations in the phase, frequency and orientation of the fringes. This confirms the importance of orientation and high frequencies, both for which two approaches were undertaken: alternative decompositions and directional wavelets.

![Figure 6: “Lena” (left), an archetypical natural image, with its Fourier transform (right)](image)
4.3 Using alternative decompositions

The Mallat decomposition scheme will only further decompose the lowpass subbands iteratively. Because of the prevalence of high-frequency components in holographic images in comparison to natural images, there will be many non-zero wavelet coefficients in the resulting highpass channels. Therefore, we investigated several alternative decompositions that further decompose the high-frequency subbands. In total, four decomposition schemes were evaluated: the Mallat decomposition, the full packet decomposition, and two intermediary variants (they can be seen on Figure 4).

The rate-distortion behaviour was evaluated at different bitrates (2.0 bpp, 1.0 bpp, 0.50 bpp, 0.25 bpp, 0.125 bpp) for the different decomposition structures and our test dataset. The results are summarized by using “Bjøntegaard delta PSNR” (BD-PSNR) [18], which is a commonly accepted metric for image coding evaluations.

The BD-PSNR converts all the measured rates in logarithmic format in order to have both rate and distortion expressed in logarithmic scale. Next, the best fitting polynomial curves of degree 3 are calculated for the measurements for each algorithm. The surface between both curves will be a metric quantifying the average distortion reduction (see Figure 8 for a visual representation of the algorithm).
The results in the tables below summarize the algorithmic performance by listing the distortion reductions in BD-PSNR of the five holograms for lossy compression, and the percentual file size reduction for the lossless case, in comparison to a classical Mallat decomposition. The 9/7 kernel was used for the lossy compression. JPEG 2000 was configured to use 32x32 sized codeblocks. We always compare the performance with the standard DWT, using the Mallat decomposition.

We observe a significant, systematic improvement when deploying the alternative decompositions, with the full packet decomposition being the best one, both for the lossy and the lossless case. The precise results can be found on Table 2. Next, we will investigate the effect of incorporating the use of directional wavelets.

![Graphs](image_url)

**Figure 9**: Rate-distortion curves (in dB PSNR) for all holograms, comparing performances across different decompositions

### 4.4 Including directional wavelets

Directional wavelets are designed to detect directionality in images. Instead of encoding every subband similarly, subbands will be split in “directional blocks” (similar to codeblocks), each of which will be encoded using the optimal direction pairs. These directions can be represented by a vector, with (1,0) corresponding to the regular wavelet transform.

However, storing the indices for every existing subband will generate a too large overhead, especially for the full packet decomposition where the number of subbands grows exponentially. Therefore, directional wavelets were only used for the three main decompositions: the three involving the successive generation of the 1LL, 2LL and 3LL subbands. Each directional vector pair combination was assessed, followed by picking the optimal pair. The set of vectors (x,y) assessed is the following:

\{(1,0), (3,1), (3,2), (1,1), (1,2), (1,3), (−1,3), (−1,2), (−1,1), (−3,1), (−3,2)\}

The blocks used for directional analysis are of the same size as the codeblocks: 32x32. All other images and parameters are the same ones used in the previous section.

A quick way to predict the effect of the directional wavelets is to determine the occurrence rate of the respective vectors. Images without prominent directionality should mostly have (1,0) vectors: if the image is very isotropic (i.e. no preferred directionality), it would be optimal to pick vectors which minimize the distance between pixels, maximizing...
their mutual correlation. On the other hand, if there is much directionality present, we expect to see other vectors occur much more often: taking advantage of the strong directionality will outweigh the benefits of taking the closest neighbouring pixels. To illustrate this, several histograms of optimal vector occurrence per directional block have been added in Figure 10. These histograms confirm the importance of directionality in off-axis holographic captures.

![Directional vector occurrence histogram](image)

**Figure 10:** Directional vector occurrence histogram, for the first 2 wavelet decomposition levels; The two leftmost histograms are from a natural image for comparison. The leftmost red bars indicate the amount of \((1,0)\) coefficients.

Table 2: BD-PSNR improvements compared to the DWT Mallat, per decomposition, with and without DADWT (Lossy), in dB. The 9x7 kernel was used.

<table>
<thead>
<tr>
<th>Lossy</th>
<th>Pack 1</th>
<th>Pack 2</th>
<th>Full Packet</th>
<th>DADWT + Mallat</th>
<th>DADWT + Pack 1</th>
<th>DADWT + Pack 2</th>
<th>DADWT + Full Packet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron</td>
<td>3.05</td>
<td>3.03</td>
<td>5.81</td>
<td>5.75</td>
<td>5.91</td>
<td>5.90</td>
<td>5.99</td>
</tr>
<tr>
<td>Erythrocyte</td>
<td>4.83</td>
<td>5.07</td>
<td>6.87</td>
<td>7.28</td>
<td>7.44</td>
<td>7.40</td>
<td>7.16</td>
</tr>
<tr>
<td>Microlenses</td>
<td>2.40</td>
<td>2.49</td>
<td>3.22</td>
<td>2.89</td>
<td>3.33</td>
<td>3.32</td>
<td>3.15</td>
</tr>
<tr>
<td>Ball</td>
<td>2.96</td>
<td>3.01</td>
<td>4.82</td>
<td>5.04</td>
<td>5.49</td>
<td>5.51</td>
<td>5.68</td>
</tr>
<tr>
<td>Scratch</td>
<td>1.78</td>
<td>1.83</td>
<td>2.62</td>
<td>1.98</td>
<td>2.31</td>
<td>2.31</td>
<td>2.33</td>
</tr>
<tr>
<td>Average</td>
<td>3.00</td>
<td>3.09</td>
<td>4.67</td>
<td>4.59</td>
<td>4.90</td>
<td>4.89</td>
<td>4.86</td>
</tr>
</tbody>
</table>

Table 3: Relative file size reduction compared to the DWT Mallat, per decomposition, with and without DADWT (Lossless), in percent (%). The 5x3 kernel was used.

<table>
<thead>
<tr>
<th>Lossless</th>
<th>Pack 1</th>
<th>Pack 2</th>
<th>Full Packet</th>
<th>DADWT + Mallat</th>
<th>DADWT + Pack 1</th>
<th>DADWT + Pack 2</th>
<th>DADWT + Full Packet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuron</td>
<td>4.2</td>
<td>3.9</td>
<td>8.0</td>
<td>9.6</td>
<td>9.5</td>
<td>9.1</td>
<td>8.3</td>
</tr>
<tr>
<td>Erythrocyte</td>
<td>4.9</td>
<td>5.4</td>
<td>8.2</td>
<td>12.4</td>
<td>11.7</td>
<td>11.3</td>
<td>10.1</td>
</tr>
<tr>
<td>Microlenses</td>
<td>1.2</td>
<td>0.7</td>
<td>-1.0</td>
<td>4.1</td>
<td>3.4</td>
<td>2.8</td>
<td>0.0</td>
</tr>
<tr>
<td>Ball</td>
<td>1.9</td>
<td>1.5</td>
<td>3.6</td>
<td>8.9</td>
<td>9.1</td>
<td>8.7</td>
<td>7.9</td>
</tr>
<tr>
<td>Scratch</td>
<td>1.8</td>
<td>1.6</td>
<td>2.4</td>
<td>2.6</td>
<td>2.8</td>
<td>2.6</td>
<td>1.9</td>
</tr>
<tr>
<td>Average</td>
<td>2.8</td>
<td>2.6</td>
<td>4.2</td>
<td>7.5</td>
<td>7.3</td>
<td>6.9</td>
<td>5.6</td>
</tr>
</tbody>
</table>

There are further improvements when combining directional wavelets with the alternative decompositions; when directional wavelets are used, all three packet decompositions approximately perform equally well on average in the lossy case.
The file size reduction for the lossless case is far larger when using directional wavelets: DADWT combined with the regular Mallat decomposition is almost invariably the best combination\(^\ddagger\).

![Graphs showing rate-distortion curves for different holograms](image)

Figure 11: Rate-distortion curves (in dB PSNR) for all holograms, comparing performances across different decompositions, with and without the DADWT.

5. CONCLUSION

Off-axis holographic recordings can be compressed more effectively by using variants on the standard JPEG 2000 compression algorithms. Based on the PSNR metric, we can draw the following conclusions:

1. Both the DADWT and the alternative decompositions do significantly improve the compression performance for lossy compression. Combining both methods gives an average improvement of nearly 5 dB Bjøntegaard delta PSNR. The gains can surpass 10dB for low bitrates (see the graphs for “Neuron” and “Erythocryte”)

2. If lossless compression is required, the best performing combination with the 5/3 integer kernel was the DADWT Mallat transform. The average file size reduction amounts to about 7.5% compared to the standard compression algorithm.

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\(^\ddagger\) The size of the overhead for the directional wavelets has been included in the calculations as well.
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