Human Visual System Inspired Color Space Transform in Lossy JPEG 2000 and JPEG XR Compression

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Abstract. In this paper, we present a very simple color space transform HVSCT inspired by an actual analog transform performed by the human visual system. We evaluate the applicability of the transform to lossy image compression by comparing it, in the cases of JPEG 2000 and JPEG-XR coding, to the ICT/YCbCr and YCoCg transforms for 3 sets of test images. The presented transform is competitive, especially for high-quality or near-lossless compression. In general, while the HVSCT transform results in PSNR close to YCoCg and better than the most commonly used YCbCr transform, at the highest bitrates it is in many cases the best among the tested transforms. The HVSCT applicability reaches beyond the compressed image storage; as its components are closer to the components transmitted to the human brain via the optic nerve than the components of traditional transforms, it may be effective for algorithms aimed at mimicking the effects of processing done by the human visual system, e.g., for image recognition, retrieval, or image analysis for data mining.

Keywords: image processing, color space transform, human visual system, bio-inspired computations, lossy image compression, ICT, YCbCr, YCoCg, LDgEb, image compression standards, JPEG 2000, JPEG XR

1 Introduction

For natural images, the correlation of the RGB color space primary color components red (R), green (G), and blue (B) is high [18]. Correlation results from the typical characteristic of RGB images and reflects that the same information is contained in two or all three components. For example, an image area which is bright in one component usually is also bright in others. Computer generated images also share such characteristic, since artificial images mostly are made to resemble natural ones. Recent image compression standards: JPEG 2000 [28,9] (as well as the DICOM incorporating JPEG 2000 [15]) and JPEG

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XR [4,10] compress independently the components obtained from an RGB image by using a transform to a less correlated color space. Although the independent compression of transformed components is not the only method for color image compression, it is the most frequently used one. It allows to construct a color image compression algorithm based on a simpler grayscale image compression algorithm. As compared to compressing the untransformed components, by applying the color space transform we improve the image reconstruction quality or the lossless compression ratio (for lossy and lossless algorithms, respectively), since without the transform the same information would be independently encoded more than one time. However, alternative approaches are known that take advantage of inter-component correlations while encoding of untransformed or transformed components [1,6,7].

In this paper we present a human visual system inspired color space transform (HVSCT) for lossy image compression. We evaluate this transform by comparing it for 3 sets of test images and 2 image compression standards (JPEG 2000 and JPEG-XR) to transforms ICT/YCbCr and YCoCg.

The reminder of this paper is organized as follows. In Section 2 we discuss properties of irreversible color space transforms and present the ICT/YCbCr and YCoCg transforms used then for comparison with HVSCT. Section 3 introduces the new transform. Section 4 contains experimental procedure, results, and discussion; Section 5 summarizes the research.

2 Color space transforms

The Karhunen-Loève transform (KLT) is an image-dependent transform that for a specific image is constructed by using the Principal Component Analysis (PCA), it optimally decorrelates the image [16,18]. The computational time complexity of PCA/KLT is in practice too high to compute it each time an image gets compressed. Instead, fixed transforms are constructed based on PCA/KLT by performing PCA on a set of typical images. Then, assuming that the set is sufficiently representative also for other images, which were not included in the set, we use the obtained fixed KLT transform variant for all images. The frequently used color space transforms, for example, the YCbCr color space transform described below, are fixed transforms constructed based on PCA/KLT; however, there are algorithms constructing a color space transform for the specific image. An adaptive selection of the transform from a large family of 60 simple transforms was proposed by Strutz [26]; performing the selection slightly increases the overall cost of the lossless color image compression algorithm. In [27], an even larger family of 108 simple transforms is presented; adaptive transform selection is performed for the entire image or for separate image regions, however, the latter approach leads to only a small further ratio improvement. Singh and Kumar [19] presented an image adaptive method of constructing a color space transform based on the Singular Value Decomposition. Although this method is of significantly greater computational time complexity, than a method which directly selects a transform from a family of simple transforms, it is still simpler than computing PCA/KLT for a given image.

The probably most commonly used color space, but the RGB space, is YCbCr. It was constructed using PCA/KLT, but with an additional requirement: the transform should contain a component that approximates the luminance perception of the human visual system [14]. YCbCr contains the Y component that represents the luminance and two chrominance components: Cb and Cr. YCbCr was constructed decades ago for video data and nowadays is used both for video and for still image compression. There are many variants of the transform between RGB and YCbCr (resulting in respective variants of the YCbCr color space). Below we present one of them, ICT (Eq. 1), with inverse (Eq. 2):

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.29900 & 0.58700 & 0.11400 \\ -0.16875 & -0.33126 & 0.50000 \\ 0.50000 & -0.41869 & -0.08131 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{1}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1.00000 & 0.00000 & 1.40200 \\ 1.00000 & -0.34413 & -0.71414 \\ 1.00000 & 1.77200 & 0.00000 \end{bmatrix} \begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix}. \tag{2}$$

ICT is defined in the JPEG 2000 standard for lossy compression [10].

Note, that if the transformed components are to be stored using integer numbers, then the transform is not exactly reversible—we say that it is irreversible or not integer-reversible. It is not a problem in a typical case of lossy coding, where distortions introduced by forward and inverse transform are much smaller than distortions caused by lossy compression and decompression. However, in the case of the very high quality coding, the color space transform may limit the obtainable reconstruction quality. The integer-reversible variants of ICT and of other transforms are constructed using the lifting scheme [2]. The reversibility is obtained at the cost of the dynamic range expansion of the transformed chrominance components by 1 bit (the dynamic range of a component is defined as a number of bits required to store pixel intensities of this component). The dynamic range expansion affects the transform applicability, since certain algorithms and implementations either do not allow or do not process efficiently images of depths greater than, e.g., 8 bits per component. Expansion may be avoided by the use of modular arithmetic (as in the RCT transform in the JPEG-LS extended standard [8]), however, such transform introduces sharp edges to transformed components, that worsen the lossy compression effects. In this research we focus on typical transforms for lossy coding—not using the modular arithmetic and not expanding the dynamic range of transformed components.

A recent YCoCg transform is an another interesting transform (forward in Eq. 3 and inverse in Eq. 4):

$$\begin{bmatrix} Y \\ Co \\ Cg \end{bmatrix} = \begin{bmatrix} 1/4 & 1/2 & 1/4 \\ 1/2 & 0 & -1/2 \\ -1/4 & 1/2 & -1/4 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{3}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 1 & -1 \\ 1 & 0 & 1 \\ 1 & -1 & -1 \end{bmatrix} \begin{bmatrix} Y \\ Co \\ Cg \end{bmatrix}. \tag{4}$$

It was obtained based on PCA/KLT constructed for a Kodak image-set (see section 4.1 for the Kodak set description); YCoCg is an irreversible variant of a YCoCg-R transform included in the JPEG-XR standard [10,14]. The YCoCg transform is significantly simpler to compute, than ICT. The former requires 15 simple floating point operations (additions, subtractions, multiplications) for forward and 8 operations for inverse transform. The YCoCg forward transform may be computed in 6 integer operations (add, subtract, and bit-shift; the latter denoted by >>):

$$t = (R + B) >> 1; \quad Y = (G + t) >> 1; \quad Co = R - t; \quad Cg = Y - t;$$

inverse in 4 additions and subtractions only:

$$G = Y + Cg; \quad t = Y - Cg; \quad R = t + Co; \quad B = t - Co;$$

3 New transform inspired by human visual system

We described in detail previously [21] the following interesting fact. A color space transform that results in a single luminance and 2 chrominance components is performed by our (i.e., human) visual system. There are three types of cone cells in our retinas that are most sensitive to three light wavelengths, these are S-cones (short wavelength with sensitivity peak in violet), M-cones (middle wavelength, sensitivity peak in green), and L-cones (long wavelength, peak in yellow). According to the common opinion, the cones simply respond to blue (S-cones), green (M-cones), and red (L-cones) light. However, this opinion is wrong not only because the cone sensitivity peaks are outside of red and blue wavelengths, but also since S-cones are sensitive to colors ranging from violet to green, whereas M-cones and L-cones are sensitive to the full visible spectrum. However, indeed the highest reaction to blue color, among all cone types, is shown by S-cones, to green by M-cones, and to red by L-cones. The response of cones is then transformed and to the brain, via the optic nerve, the below three components are transmitted:

– the luminance computed as a sum of responses of L-cones and M-cones,
– the red minus green color component (a difference between responses of L-cones and M-cones),
– and the blue minus yellow color component (a difference between response of S-cones and a sum of L-cones and M-cones responses, which may be also seen as a difference between the response of S-cones and the computed luminance).

For brevity, above mentioned were only certain aspects of human visual system reduced to essentials; for further details the Reader is referred to [5] and references therein.

In [21] we have investigated an integer-reversible color space transform for lossless image compression modeled on a transform performed by the human visual system (LDgEb); it resulted in very good average lossless compression ratios for several image sets and compression algorithms. The same transform has been presented by Strutz as a special case (denoted $A_{4,10}$) of a large family of simple integer-reversible transforms [27]. Here, evaluation was based on counting how many times given transform resulted in the best lossless ratio for an image from the test-set employed. Interestingly, while for a diverse set of photographic images it was the second one most often resulting in best ratio, for a more homogeneous set it has never been the best one. LDgEb is simple to compute, but as most of the transforms for lossless coding, it causes dynamic range expansion of chrominance components. In this research, based on LDgEb, we propose an irreversible color space transform for lossy image compression, named HVSCT. The new transform originates from the human visual system and is normalized to obtain the same dynamic range after the transform, as before it. In the HVSCT transform (Eq. 5, inverse presented in Eq. 6):

$$\begin{bmatrix} Y \\ Cd \\ Ce \end{bmatrix} = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 1/2 & -1/2 & 0 \\ -1/4 & -1/4 & 1/2 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}, \tag{5}$$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -1 & 0 \\ 1 & 0 & 2 \end{bmatrix} \begin{bmatrix} Y \\ Cd \\ Ce \end{bmatrix} \tag{6}$$

the luminance is, as in humans, a sum of two longer wavelength components, but multiplied by 0.5: $Y = (R+G)/2$, chrominance components are normalized differences: between two longer wavelength components $Cd = (R - G)/2$ and between the shortest wavelength component and the luminance $Ce = (B - Y)/2$.

The HVSCT forward transform is even simpler to compute than YCoCg, since it may be computed in 5 integer operations (add, subtract, bit-shift):

$$Cd = (R - G) >> 1; \quad Y = R - Cd; \quad Ce = (B - Y) >> 1;$$

inverse HVSCT, as inverse YCoCg, requires 4 additions and subtractions:

$$R = Y + Cd; \quad G = Y - Cd; \quad B = Y + Ce + Ce;$$

4 Experimental evaluation

4.1 Procedure

In the evaluation we included the ICT, YCoCg, and HVSCT transforms; we also report results for untransformed RGB images. Transforms were applied with the colortransf tool, version 1.1[1]; ICT was performed using real (double) numbers, whereas other transforms were implemented using integers. If a transformed

[1] http://sun.aei.polsl.pl/~rstaros/imgtransf/colortransf/

pixel component exceeded its nominal range, then it was corrected to its nearest range limit. After the color space transform was applied to an image, the resulting components were compressed as a single image (all components together, with disabled color space transform of the compression algorithm). We measured resulting compression ratio in bits per pixel [bpp] (bitrate) and, after decompression and inverse color space transform, the PSNR image quality [dB] in the RGB domain.

We evaluated the effects of the color space transforms on image quality of JPEG 2000 and JPEG XR compression. JPEG 2000 is an ISO/IEC and ITU-T standard lossy and lossless image compression algorithm based on discrete wavelet transform (DWT) image decomposition and arithmetic coding [28,9]. JPEG XR is a recent ISO/IEC and ITU-T lossy and lossless standard algorithm designed primarily for high quality, high dynamic range photographic images; it is based on discrete cosine transform image decomposition and adaptive Huffman coding [4,10]. We used the JasPer implementation of JPEG 2000 by Adams, version 1.900[2] and a standard reference implementation of JPEG XR [11]. The former allows setting the desired bitrate, to which the actual one is close (not greater than). The JPEG XR implementation allows setting the quantization value for all components (we used this option) or for each component individually, but the resulting bitrate depends significantly on the image contents. We report average PSNR for bitrates from 0.25 bpp to 6 bpp. Since JPEG 2000 and JPEG XR for the below sets of images obtain average lossless ratios from 9.5bpp to 13.3bpp, the 6 bpp may be considered a high quality or nearly-lossless bitrate setting. The compression was performed with several (16) bitrate/quantization settings. Then, in the cases of both algorithms, to obtain average PSNR for a group of images at a desired bitrate, for each image the PSNR was interpolated (polynomial 3-point interpolation) based on results obtained for 3 bitrates nearest to the desired one.

The evaluation of transforms was performed for the following sets of 8-bit RGB test images:

- Waterloo[3] – a set (“Colour set”) of color images from the University of Waterloo, Fractal Coding and Analysis Group repository, used for a long time in image processing research. The set contains 8 natural photographic and artificial images, among them the well-known ”lena” and ”peppers”, image sizes vary from 512×512 to 1118×1105.
- Kodak[4] – a set of 23 photographic images released by the Kodak corporation, the set is frequently used in color image compression research. All images are of size 768×512.
- EPFL[5] – a recent set of 10 high resolution images used at the École polytechnique fédérale de Lausanne for evaluation of subjective quality of JPEG XR [3]. Image sizes from 1280×1506 to 1280×1600.

[2] http://www.ece.uvic.ca/~mdadams/jasper/
[3] http://links.uwaterloo.ca/Repository.html
[4] http://www.cipr.rpi.edu/resource/stills/kodak.html
[5] http://documents.epfl.ch/groups/g/gr/gr-eb-unit/www/IQA/Original.zip

4.2 Results

In Tables 1 and 2 for JPEG 2000 and JPEG XR, respectively, we present average PSNR calculated for images from all groups; images were transformed with the ICT, YCoCg and HVSCT transforms and we also report the results of coding of untransformed RGB images. Due to limited space the data is in Tables presented for certain bitrate/quantization settings only, however, results for all the settings are presented in Fig. 1 (in panel A for JPEG 2000 and panel B for JPEG XR). Results are similar for both algorithms. Average PSNR image quality for low bitrates is for all 3 transforms close to each other and better than for untransformed RGB by about 2-3.5dB (depending on the bitrate). From about 1bpp, the PSNR of YCoCg and HVSCT transformed images is still close to each other and better than for RGB, but the results of the ICT transform get closer to results obtained without a color space transform.

Table 1. JPEG 2000 average PSNR for all images from all groups.

Transform	Bitrate								
	0.25	0.50	1.00	1.50	2.00	3.00	4.00	5.00	6.00
RGB	25.798	28.008	30.847	32.872	34.516	37.151	39.242	41.083	42.655
ICT	27.790	30.559	33.881	36.001	37.562	39.737	41.388	42.550	43.630
YCoCg	27.846	30.667	34.087	36.342	38.063	40.611	42.735	44.512	46.037
HVSCT	27.639	30.402	33.781	36.046	37.784	40.351	42.487	44.223	46.048

Table 2. JPEG XR average PSNR for all images from all groups.

Transform	Bitrate								
	0.25	0.50	1.00	1.50	2.00	3.00	4.00	5.00	6.00
RGB	25.708	28.019	30.953	33.028	34.680	37.299	39.448	41.332	43.088
ICT	28.339	30.752	34.088	36.176	37.726	39.983	41.503	42.561	43.331
YCoCg	28.421	30.908	34.430	36.723	38.511	41.249	43.287	44.816	46.016
HVSCT	28.250	30.785	34.295	36.590	38.360	41.127	43.209	44.805	46.087

Good performance of the new transform may be surprising considering that, as opposed to others, it has not been designed based on analysis of digital images, but simply adopted from the analog transform of the human visual system. On the other hand, digital images are acquired or constructed for the human visual system, therefore digital image representation as well as algorithms processing images may be indirectly influenced by our visual system. The close relation of HVSCT to the human visual system may be beneficial for other image processing

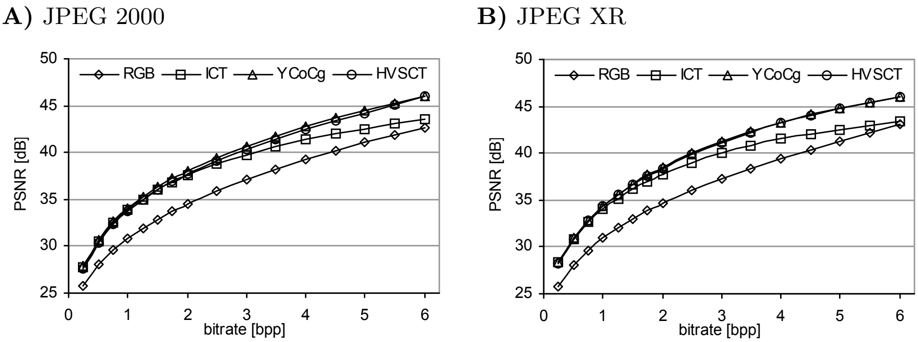

Fig. 1. JPEG 2000 (A) and JPEG XR (B) average PSNR for all images from all groups.

algorithms that exploit color space transforms and are aimed at mimicking the effects of image processing and analysis done by the human visual system, e.g., face or skin detection algorithms [12,13].

In order to compare effects of color space transforms on JPEG 2000 and JPEG XR more thoroughly, in Fig. 2 for each compression algorithm and for each image group we present PSNR relative to PSNR obtained without a color space transform. For a given transform its relative PSNR was calculated by subtracting from its absolute PSNR the PSNR obtained in the case of RGB. Dissimilarities in relative performance of transforms are noticeable rather between image groups, than between compression algorithms. Generally, results of HVSCT are close to results of YCoCg also for individual image groups. While for the lowest bitrates HVSCT is close, but worse than others, for high bitrates in many cases it obtains the best PSNR. Let's look at the results for the Waterloo group of images (Fig. 2, panels A and B). This is the oldest group and only this group contains both natural and computer generated images; the latter differ significantly from natural continuous-tone images, as some of them are dithered, have sparse histograms of intensity levels [17,20], or are composed from images and text. For the Waterloo images, YCoCg is better than HVSCT at all bitrates by from 0.17 to 0.79dB. For more recent Kodak and EPFL continuous tone natural images (Fig. 2, panels C to F), the difference between HVSCT and YCoCg in average PSNR is at most 0.44dB (0.20 for JPEG XR). Here, YCoCg is better up to a certain threshold (depending on algorithm and set from 1bpp to 5.5bpp), above which HVSCT obtains better PSNR.

We did not perform any systematic subjective assessment of transform effects on reconstructed image quality, however, in the cases of several images, which were viewed on a regular LCD IPS monitor, for both algorithms there was no noticeable quality difference between ICT, YCoCg, and HVSCT, while images compressed in RGB domain at lower bitrates contained more apparent artifacts and less details.

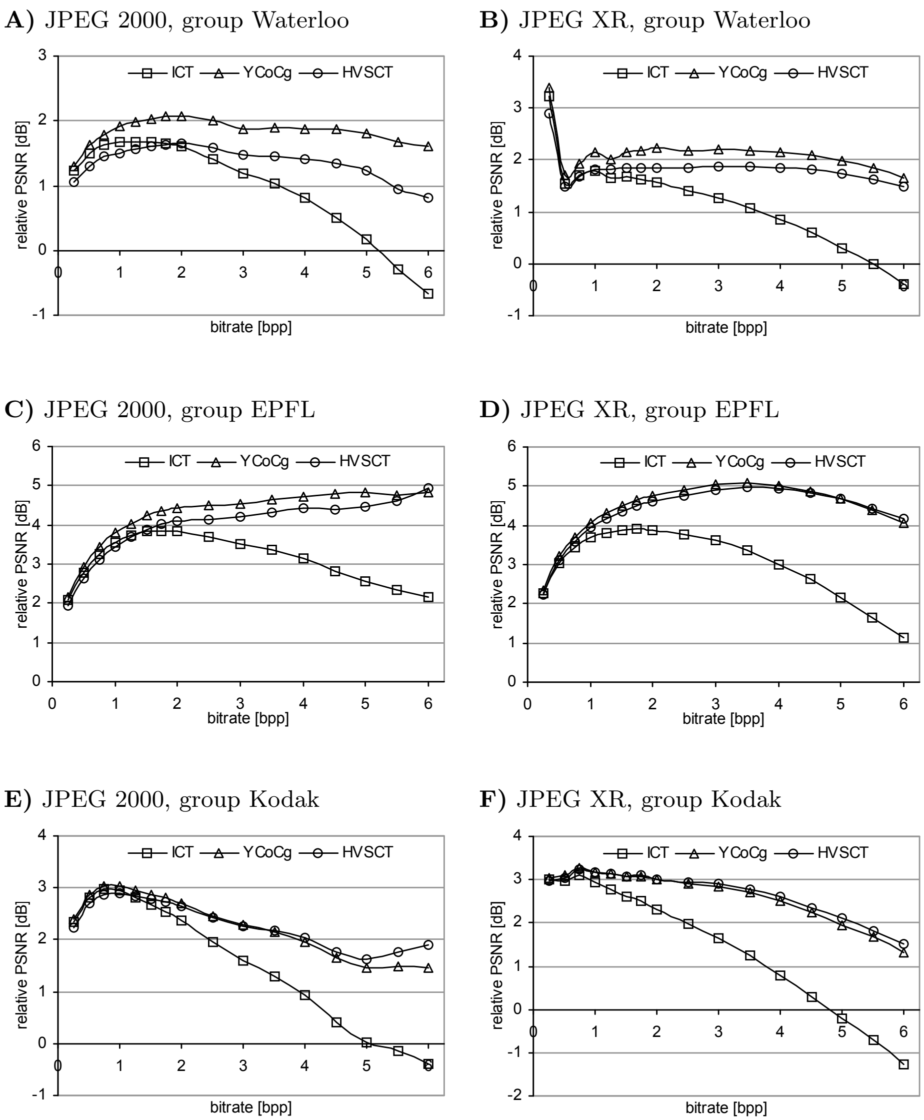

Fig. 2. JPEG 2000 and JPEG XR average PSNR image quality for individual groups of images, relative to quality obtained in the case of untransformed RGB.

5 Conclusions

We presented the bio-inspired HVSCT transform for lossy image compression, which originates from the analog transform performed by the human visual system. The transform does not expand the dynamic range of transformed components and is of very low computational time complexity (5 simple integer operations per pixel for forward transform, 4 for inverse).

We evaluated effects of employing the new transform in JPEG 2000 and JPEG XR compression for 3 popular sets of test images and compared it with the ICT/YCbCr and YCoCg transforms. Although, as opposed to others, HVSCT was not designed based on analysis of digital color images, with respect to PSNR it obtains results close to the recent YCoCg transform. In most cases, for the greatest part of the tested bitrate range (0.25 to 6 bpp) YCoCg results in little better PSNR than HVSCT, whereas ICT in significantly worse. HVSCT appears the most useful in high quality lossy image compression, or in near-lossless compression, since at the highest bitrates it usually is the best among the tested transforms.

In order to improve the effects of HVSCT, we plan to apply to it the RDLS method. RDLS ia a modification of the lifting scheme [2] that was found effective for improving the lossless compression ratios in the cases of several integer-reversible lifting-based color space transforms [23,24] and the discrete wavelet transform [22,25]. HVSCT may be implemented using the lifting scheme; the good results of RDLS obtained for lossless coding indicate that it may be also effective for the near-lossless compression. As compared to color spaces traditionally used in various algorithms in the digital image processing domain, like retrieval or recognition, that are aimed at mimicking the effects of processing happening in the human visual system, the components of HVSCT are closer to the components transmitted to the human brain via the optic nerve. This opens a promising field of future research. Checking whether by using HVSCT instead of traditional color space transforms the results of such algorithms will get closer to results we expect from experience with our own visual system is certainly worthwhile. Other potential fields of further research are subjective evaluation of image quality after the HVSCT followed by the lossy compression as well as application of HVSCT to video data.

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