# Efficient Compression of Hyperspectral Images Using Optimal Compression Cube and Image Plane

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## Abstract

Hyperspectral (HS) images (HSI) provide a vast amount of spatial and spectral information based on the high dimensionality of the pixels in a wide range of wavelengths. A HS image usually requires massive storage capacity, which demands high compression. HS images can be deemed as three dimensional data cubes where different wavelengths (W) form the third dimension along with X and Y dimensions. To get a better compression result, spatial redundancy of HS images can be exploited using different coders along the X, Y or W direction. This article focuses on reducing HS image redundancy by rearranging HS images, and proposes a directionlet based compression scheme calculating the optimal compression plane (OCP) to adapt for the best approximation of the geometric matrix. The OCP, calculated by spectral correlation, is used to predict and determine which reconstructed plane can reach higher compression rates while minimizing data loss of hyperspectral data. Moreover, we also rearrange the 3D data cube into different 2D image planes and investigate the compression ratio using different coders. The schema can be used for both lossless and lossy compression. Our experimental results show that the new framework optimizes the performance of the compression using a number of coding methods for HSIs with different visual content.

## Proposed Techniques


Fig. 1 A hyperspectral image (left) with different slices corresponding to wavelength and an example of intensities (right) for real and plastic objects in different wavelengths.

Examples of a HS image and intensity variations in different type objects are shown in Fig. 1 where we can see different slices of a HS image in different wavelengths from 400 to 720nm (left) and intensity differences in wavelengths for real and plastic objects.

Finding efficient geometric representations of images is one of the key problems to improving HS image compression. A HS image can be reconstructed in 6 directions of 3D data cube, *XY W* (in this direction normally HS images are captured, stored, and display), *YX W*, *WX Y*, *XW Y*, *WY X*, and *YW X*. Although there are six directions we can form a HS 3D data cube, our experiments using different coders find that two reversed data cubes such as *W XY* and *XW Y* provide the same rate-distortion performance. Thus, in our experiment we only use three directions (such as *XY W*, *WX Y* , and *WY X*) to find the OCC. In addition to 3D formation we also explore directional representation in a 2D dimension $(XY)\times W$, $(YX)\times W$, and $(WX)\times Y$ where the two dimensions in brackets form the first dimension and the third dimension forms the second dimension in an image.

### 2.1 3D Plane Reconstruction

In the sense of data structure, a HS image contains extensive redundancy among *X* (i.e. a spatial dimension), *Y* (i.e. the other spatial dimension), and *W* (i.e. the wavelength dimension). Therefore, we need to determine higher redundancy along a different axis before we compress each HS image. In the first step, we aim to construct a 3D cube along the different axis of a HS image. Fig. 2 shows a HS image named as Vase in different cubic forms. From the figure, we can easily observe that the spatial and spectral correlations in *XY W*, *WX Y* and *WY X* cubes are different. Thus, a specific coder may exploit the redundancy of a cube better than other coders which justifies the rearrangement of a HS image into different 3D cubes.

### 2.2 2D Plane Reconstruction

Three examples of 2D images of the same HS image.
In our data set, a HS image has 1040139261 resolutions
where *X* = 1040, *Y* = 1392, and *W* = 61.

We can form 2D images in different directions of a HS image in
X × (Y W) i.e., 104084912(=139261),
Y × (X W) i.e., 139263440(=104061), and
W × (X Y) i.e., 611447680 (=10401392).

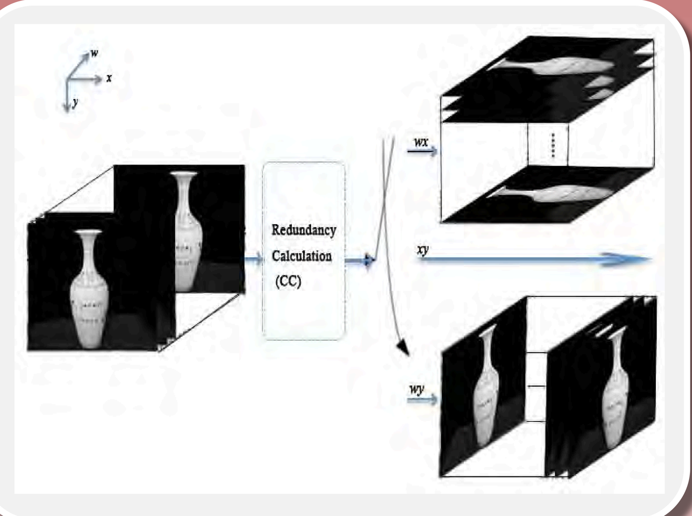


Fig.2 Different 3D data cubes (*XY W*, *WX Y*, *WY X*) from where the proposed optimal compression cube algorithm selects the best cube based on the cross correlation, the proposed OCC algorithm and cross correlation equation is defined in Section 2.3.

### 2.3 OCC Determination from 3D cubes

OCC determination will help to choose an optimal cube. The cross-correlation coefficient (CC) of *n-th* slice $P_n$ is formulated as follows:

$$CC_n = \frac{\sum_{i,j}((p_n(i,j)-\overline{p_n})(S(i,j)-\overline{S}))}{\sqrt{\sum_{i,j}((p_n(i,j)-\overline{p_n})^2\sum_{i,j}(S(i,j)-\overline{S})^2}}$$

where *S* is a median slice of a HIS cube and $P_n$ is the average pixel intensities of *n-th* slice.

## Experiments

We confirm that the natural cube is the best compression cube. HEVC and JPEG2000 are better encoders where HEVC provides more consistent performance in different directions compared to JPEG2000 as shown in Fig 3. Experimental results also show that our proposed optimal compression cube prediction technique can predict the optimal 3D cube successfully in most cases. The proposed OCC framework is compatible with any compression encoders and decoders.

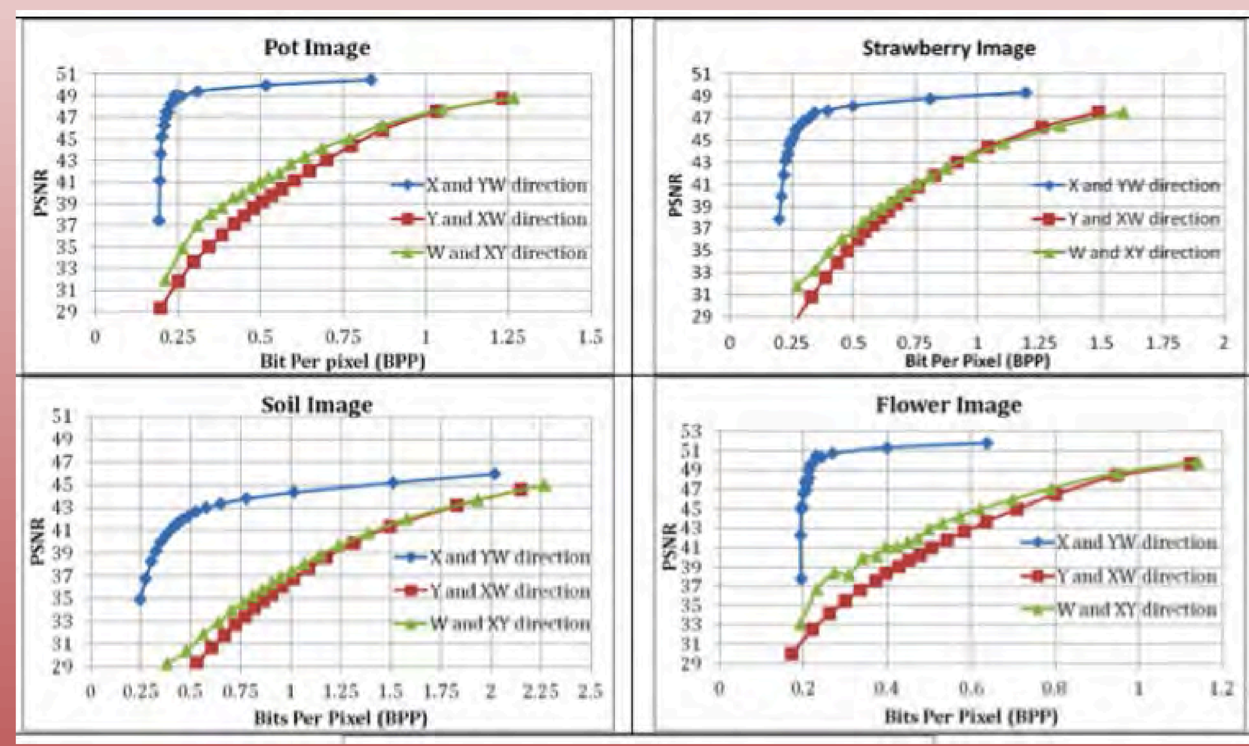


Fig.3 Rate-distortion performance of five standard hyperspectral images using JPEG coder on three different 2D arrangements: (i) X and YW i.e., 1040 84912, (ii) Y and XW i.e., 1392 63440, and (iii) W and XY i.e., 611447680.

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