A walk through spectral bands: Using virtual reality to better visualize hyperspectral data

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Abstract. One of the basic challenges of understanding hyperspectral data arises from the fact that it is intrinsically 3-dimensional. A diverse range of algorithms have been developed to help visualize hyperspectral data trichromatically in 2-dimensions. In this paper we take a different approach and show how virtual reality provides a way of visualizing a hyperspectral data cube without collapsing the spectral dimension. Using several different real datasets, we show that it is straightforward to find signals of interest and make them more visible by exploiting the immersive, interactive environment of virtual reality. This enables signals to be seen which would be hard to detect if we were simply examining hyperspectral data band by band.

Keywords: hyperspectral imaging, virtual reality, data visualization, chemical signal visualization

1 Introduction

The visualization of large data sets in high dimensions still poses a major challenge. The ultimate goal is to convert these observed, or simulated, phenomenon into rules, laws or principles. This is the process of knowledge discovery from data. Recent advances in virtual reality (VR), coupled with enhancements in computational power, present the possibility of a new paradigm for data exploration. This will involve the combination of an expert user interacting with mathematical algorithms that characterize information in the observations. The final objective is the guided navigation of high-dimensions in order to extract fundamental insights into the data.

Unlike RGB (red-green-blue) data which has 3-bands and which can be visualized in 2-dimensions by exploiting our trichromacy (i.e. our color vision), most hyperspectral data is inescapably 3-dimensional by virtue of having many more spectral bands (commonly more than 150). In order to overcome the challenge of analyzing such data, algorithms and software have been developed which either allow the user to scan through the data and selectively display different bands [3], selects the bands automatically to try to maximize some information criteria [9, 5], or treats band selection as a dimensionality reduction problem [15, 14, 6].

In this paper we take a different approach. Instead of trying to develop methods which condense the information of a hyperspectral image into a digestible 2-dimensional format, we instead embrace the 3-dimensionality of hyperspectral data by choosing to use VR where we can visualize the data cubes in full. We propose this framework not only because it fully leverages our innate 3-dimensional visual abilities, but also because it provides for an immersive experience where the user's full attention can be directed to exploring the data. The idea of VR has a history dating back to 1965 [13]. It has only been in the last 15 years however that hardware capabilities have improved to the point that many of the envisioned applications of VR have started to become a reality. In general, VR is a good tool for exploring data where the addition of a third spatial dimension for exploration provides significant improvements in understanding. A few examples of applications of VR include [7, 11, 10, 8, 12, 1].

We see at least two advantages to visualizing hyperspectral data using VR. The most obvious has already been pointed out; in VR, researchers would be exploring the data in its natural dimension, without any reductions necessary. The difference here is equivalent to the difference between giving a physician a collection of 2-dimensional images of slices of a human heart versus giving the physician the ability to look at that stack of images formed into a single 3-dimensional representation of that heart. In VR we expect explorations of hyperspectral data to not only be more thorough but also vastly more efficient and accessible. The second benefit to moving the analysis of hyperspectral data to the virtual realm is that it will make it easier for researchers to collaborate in real time regardless of whether they are in the same location or not [16].

2 Background

2.1 Hyperspectral data

The hyperspectral data that we use in this paper comes in the form of a *data cube*, that is an $n \times m \times b$ array of numbers where n, m, b are positive integers. The first two coordinates correspond to the *spatial dimensions* while the values of n and m denote the *spatial resolution* of the data cube. The third coordinate corresponds to the *spectral dimension* with b denoting the number of *spectral bands*. For each k with $1 \leq k \leq b$, the k^{th} band is represented by an $n \times m$ array that captures the intensity of energy in that particular wavelength across the scene.

2.2 Virtual reality for data visualization

Virtual reality utilizes a combination of hardware and software to create an immersive and explorable environment in which a user can interact with data. Its immersive environment affords users a unique and intuitive perspective of structural relationships and scale.

We used BananaVision software developed at Colorado State University to load and visualize our hyperspectral data in VR. BananaVision is a networked, multi-user virtual reality tool that renders both human anatomical learning models as well as medical images (CT, PET/CT, MRI, MEG, NIfTII) for the creation of instructional content and clinical evaluation. The BananaVision software takes "stacks" of 2-dimensional images and volumizes them to give a 3-dimensional representation that can be explored in virtual reality. The volumetric data is colored by the positive scalar value attached to each position in the data cube. In the case of hyperspectral data, the coloring is thus determined by the spectral intensity values at each point in the cube.

Without manipulation, a data cube would be presented in VR as a solid object and we would only be able to study its exterior (the edges of each band as well as the first and last band). In order to begin to segment out interesting structures within the cube we need to: slice the cube to expose intensity values in the interior, make certain locations in the cube more or less transparent, and choose a coloring scheme (based on intensity) which helps us to discriminate between different structures.

3 Example visualizations

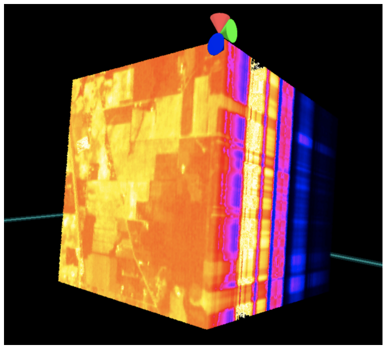
In this section we describe and provide pictures of the application of VR to two hyperspectral data sets. These explorations were carried out using a machine running an Nvidia 1080 Ti graphics card.

3.1 Indian Pines

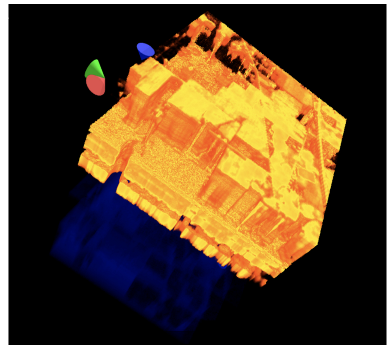
The Indian Pines data set consists of 220 spectral bands at a resolution of 145×145 pixels (that is, a $145 \times 145 \times 220$ data cube). We use a corrected data set that has bands from the region of water absorption removed, resulting in 200 remaining spectral bands.[3] The data was collected with an airborne visible/infrared imaging spectrometer (AVIRIS) at the Indian Pines test site in Indiana [2]. The scene contains various classes, such as woods, grass, corn, alfalfa, and buildings.

In Figure 1 (a) we show what this data looks like with the default visualization settings in VR. As described above, the cube is colored by the intensity at a location in the cube. As can be seen, without adjusting the display settings, the only parts of the data cube that we can examine are the boundary faces. In Figure 1 (b) we have removed certain bands, thresholded out certain intensity levels, and chosen to make other intensity values more transparent. The result is that we can essentially carve out the spectral information related to some of the features from the cube. For example, at least some of the plateau-like structures seen in (b) correspond to agricultural fields with different kinds of crops. The structures that resemble trees at the far top corner of the cube do not correspond to a labeled ground truth class. This is an example of a feature that stands out in VR that might warrant further examination.

[3] The data is available at: http://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes.



(a)



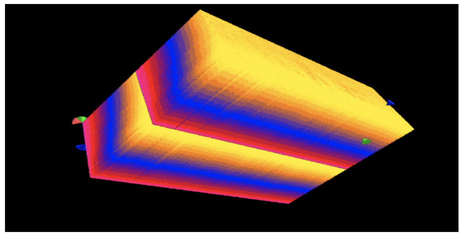
(b)

Fig. 1: The Indian Pines hyperspectral data cube as seen in virtual reality. (a) Shows how the cube appears when it is first loaded (that is, in the default display settings). The yellow rectangle is the first band. One can see the outline of agricultural fields. (b) Shows what the cube looks like after we have removed certain bands, made completely transparent positions in the cube with intensity values above or below certain thresholds, and selectively colored and assigned transparency values to the remaining intensity values. As can be seen, using these relatively simple operations we can begin to chisel out figures of interest in the cube. The agricultural fields in (a) for example, now stand out in 3-dimensions as plateau-like structures in (b).

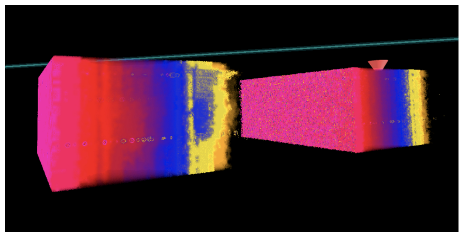
3.2 Chemical plume detection

In this section we give an example of VR applied to hyperspectral data containing a chemical simulant release. The data set that we use is the Johns Hopkins Applied Physics Lab FTIR-based longwave infrared sensor hyperspectral dataset [4]. This dataset consists of several hyperspectral videos showing a chemical simulant release. We will consider two cubes from a video showing the release of the chemical simulant sulfur hexafluoride (SF_6). One cube was taken before the release of the chemical simulant, the other was taken after and contains the chemical signal. Each data cube consists of 129 spectral bands with spatial resolution 128×320 (for a data cube of size $128 \times 320 \times 129$). In order to make the comparison between these with both visible simultaneously, we concatenate them along the spectral dimension. In Figure 2 (a) we show what the two concatenated data cubes look like in VR with default settings. The left cube in both (a) and (b) is the one that contains the chemical release. While this is not immediately obvious in Figure 2 (a), with some straight-forward intensity thresholding, color shifting, and cube slicing the chemical release becomes apparent as seen in Figure 2 (b). The chemical plume can be seen in the left cube taking the form of the blue nodule.

That we can find the chemical plume relatively easily in VR for this example is significant. It is non-trivial to find this plume by scanning through bands in



(a)



(b)

Fig. 2: Two cubes from the Applied Physics Lab FTIR-based longwave infrared sensor hyperspectral dataset, concatenated along the spectral dimension. One cube contains a chemical release of the simulant SF_6 while the other does not. It is not obvious from (a) which cube contains the chemical release. After some straight-forward intensity thresholding, color shifting, and cube slicing, the chemical release becomes apparent (b) as the blue nodule in the left cube (the spectral dimension from this viewpoint runs horizontally).

2-dimensions. We believe that our results here point toward hyperspectral data being a promising domain in which to apply VR.

4 Conclusion

In this paper we proposed the use of virtual reality as a tool to explore hyperspectral data cubes. We showed that virtual reality allows one to leverage human's innate 3-dimensional spatial ability to explore this type of data.

We end by noting some features that we believe would be useful in future VR software designed specifically for the purpose of studying hyperspectral imagery. These include: the incorporation hyperspectral specific data within the VR environment, the ability to extract spectral curves from within the VR environment, the ability to load and independently move multiple data cubes at once, and the ability to apply selected algorithms (such as wavelet or Fourier transforms) to the data cube within VR.

We speculate that the future development of geometric and topological algorithms for data analysis, such as Self-Organizing Mappings, may benefit from the ability to visualize high-dimensions using VR as a tool.

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