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# RSVP: Remote Sensing Visualization Platform for Data Fusion

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## Abstract

Remote sensing involves the acquisition of data in terms of images, point clouds and so on. One of the major challenges with remote sensing datasets is managing and understanding the massive amounts of data that is collected. In many instances, scientists acquire data for the same region using varied sensing devices. Scientists would like to fuse and examine this data acquired from different sensing devices to further explore the region under investigation. Immersive visualization has emerged as an ideal solution for three-dimensional exploration of multimodal remote sensing data. The ability to manipulate data interactively in true 3D (using stereo) with interfaces designed specifically for the immersive environment can significantly speed up the exploration process. We have developed a visualization platform that facilitates the fusion of multiple modalities of remote sensing data and allows a scientist to learn more about the data obtained from different sensing devices. It is currently being used in research labs at Idaho State University and at the Idaho National Labs.

**Index Terms:** K.6.1 [Management of Computing and Information Systems]: Project and People Management—Life Cycle; K.7.m [The Computing Profession]: Miscellaneous—Ethics

## 1 Introduction

Remote sensing, as defined by Jensen [10], is the "art and science of obtaining information about an object without being in direct contact with the object." It can be further refined to the gathering of data from a distance, frequently in the form of images or discrete points to learn more about the world. Remote sensing has multiple applications in fields such as biology, defense, environmental measurements such as change in vegetation over time, aerial traffic control and so on. Sensors are classified as *active* sensors or *passive* sensors. Active sensors rely on emitting energy (electromagnetic energy in most applications) followed by measuring and analyzing the reflected response of the signal. Passive sensors on the other hand detect energy emitted or reflected by a nearby object or a surrounding area. In most situations, the amount of data collected by these sensors is massive and obtaining a reasonable understanding of the data can be incredibly hard. Some of the problems that geoscientists face are around examination and exploration of such large datasets. Ideally, scientists would like to explore specific trends and obtain insight through the refinement of their mental model by interacting with their data.

Research has shown that exploring and eventually obtaining insight can be facilitated and, in some cases, accelerated using scientific visualization techniques [11]. Research in the field of scientific visualization has dealt with challenges of large data visualization as well as interactive exploration of data for an improved understanding [13]. Desktop-based visualization solutions may be sufficient for regions where the data is localized and trends/features can be easily seen (for e.g., medical visualization, information visualization). In situations, where the amount of data collected or generated as a result of a simulation is huge and spread over a large geographical region, desktop-based solutions can quickly become unwieldy. Research has shown that users have a hard time navigating 3D scenes using standard interfaces developed for a desktop [12]. Particularly, tasks surrounding selection, according to the taxonomy by Amar et al. [1], such as *retrieve value* and *correlate* can be extremely challenging and may lead to frustration as well as a drop in user performance. *Immersive visualization* allows scientists to visualize their data in stereoscopic 3D with the ability to fly over their data and examine regions of interest. The ability to interactively explore data in an immersive environment can provide users with a faster, better understanding of data with potential improvements in performance over desktop applications depending on the task being performed [9]. Immersive visualization though is not sufficient [19] since scientists need to be able to interact with their data in an easy, intuitive manner that includes being able to transform the data, measure distances and automatically detect and highlight user specified features.

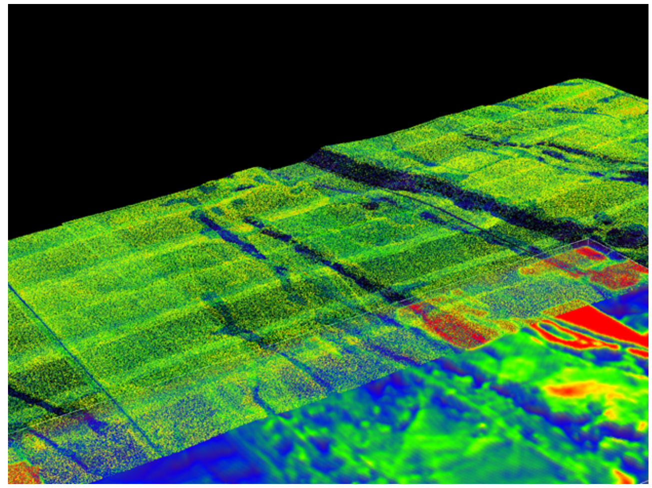

Figure 1: Overview of the fused LiDAR and hyperspectral visualization. The LiDAR point cloud is on top of the hyperspectral imagery that can be seen at the bottom. The LiDAR points are colored using height as a means for classification. The hyperspectral data is being rendered as a volume.

We have developed an immersive visualization platform that allows the fusion of remote sensing data acquired from two different modalities. Our platform, Remote Sensing Visualization Platform (RSVP) allows users to load hyperspectral imagery as well as LiDAR data acquired for the same geographical region. Hyperspectral imagery is a form of remote sensing containing many bands (images) each at a slightly different wavelength over a continuous

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interval of the electromagnetic spectrum. LiDAR (Light Detection and Ranging) is a form of active remote sensing using laser pulses to map an area, creating a 3D point cloud. Scientists are interested in examining these modalities in conjunction to learn more about a region and, in our case, the characteristics of the local vegetation [2, 23].

The features of RSVP include automatic registration of the hyperspectral imagery and LiDAR data, volume rendering of the hyperspectral image stack along with the LiDAR data, orthogonal views of the hyperspectral image stack to allow exploration of profiles in a certain region, map three user-defined hyperspectral levels to RGB values (as is the standard practice in remote sensing) as well as user interface capabilities to vary the elevation of the hyperspectral slice for correlation with the LiDAR data.

## 2 Related Work

Immersive environments have made interactive exploration in stereoscopic 3D feasible. The CAVE$^{TM}$, 3D TV's as well as research solutions such as the IQ-station [27] have given the end user the ability to experience content and data in 3D. A CAVE$^{TM}$can be particularly expensive and may not be accessible to small or even medium sized research groups, whereas an IQ-station can provide a similar immersive experience at a smaller scale. Sherman et al. [27] developed the low-cost immersive solution (IQ-station) that enables small research teams of 3 to 4 individuals to explore their data in an immersive virtual reality environment. RSVP is built on the VRUI VR toolkit [21, 18] and leverages the ability of the virtual reality toolkit to make use of the native user interfaces for a range of environments from the desktop to the IQ-station to the CAVE$^{TM}$.

Immersive visualization has made it possible for geoscientists to examine and interpret large amounts of data captured from various devices. A desktop environment can provide interactive visualization, but the interaction paradigm is mostly in terms of a keyboard and mouse. Navigating in a 3D environment with a interface elements defined for a 2D environment is particularly challenging and can pose problems with user selection, specification and manipulation of data [25]. On the other hand, interacting directly with data in a stereo environment with 3D input devices can provide a greater handle on interaction in terms of "isolation and extraction of features [20] ." Gruchalla [9] explored the use of immersive environments for path tracking and found that users were faster and more accurate when using an immersive system rather than a desktop version of their system. Di Carlo [4] developed a VR toolkit that produced various 3D representations of the same data and allowed users to interact with them in an immersive environment.

LiDAR (Light Detection And Ranging) is one of the most widely used data formats in the remote sensing domain. The amount of data acquired can easily range from a few million to sometimes even billions of points in a single dataset. The data is mostly visualized using triangulated surface representations in software such as ArcGIS [6]. It is widely used for segmenting large regions [22], building reconstruction based on point set acquisition [7, 26] and many other applications.

Visualizing such large amounts of data at interactive frame rates can be particularly challenging. Gardner et al. [8] developed a non-immersive system for analysis of LiDAR data. Even though their system was non-immersive, they found that 3D visualization of the data was extremely useful for examining features in the data and analyzing structures within. They mention the need to develop more tools for annotating and investigating details in such huge datasets. To address problems surrounding such massive datasets, Kreylos et al. [20] developed a out-of-core multiresolution rendering technique that decomposes the data using an octree data structure to provide view-dependent interactive rendering of large point cloud data. The data is preprocessed to create a multiresolution octree that can then be used as input to the interactive immersive application. Recently, Kovac and Zalik [17] developed a two-pass point based rendering technique that uses elliptical weighted average filtering [29] to address problems associated with aliasing.

## 3 Approach

In order to facilitate interactive exploration of data in an immersive environment, we decided to develop a system that could allow scientists to load both the hyperspectral imagery and the LiDAR point cloud data. We primarily worked on an IQ-station [27], but our software has also been extensively tested and used in the 4-sided CAVE$^{TM}$at the Idaho National Labs.

To facilitate exploration and correlation, we developed the remote sensing visualization platform (RSVP) that loads in the LiDAR data and allows users a variety of different options for examining the hyperspectral imagery. As of now, the hyperspectral image stack can be visualized (i) as a single greyscale slice with a single hyperspectral image mapped to the quad or (ii) as a single slice with three user-specified hyperspectral levels mapped to the Red, Green and Blue component of an image or (iii) as three orthogonal slices to examine the profile of the hyperspectral stack in x-, y-, and z-directions and (iv) volume visualization techniques with the ability to classify various regions using a transfer function. Figure 1 shows an overview of the current version of RSVP with the LiDAR data on top and the hyperspectral imagery at the bottom. The LiDAR data has been colored based on its height to perform some basic classification of the point cloud.

### 3.1 Data and Tasks

Based on conversations with scientists in our research team, we realized that one of the most frequent tasks that geoscientists perform is the correlation of data obtained from various modalities and to be able to make deductions based on that. In addition, we identified that there are scenarios where they would like to explore the entire hyperspectral stack and identify patterns in the stack. We provide volume visualization and orthogonal slice views to facilitate that task.

The data was collected for two specific sites:

1. China Hat Site: This is an area in Idaho (near Soda Springs) which has several interesting features. There are fault scarps in the region which look like deep grooves in the area. Another feature is China Hat itself which is a rhyolite dome covered in trees. The dataset was tested at various resolutions of each slice (Small - 256*106*123, Medium - 512*202, 123 and Original - 1024*424*123). Data was provided by Lucas Spaete from the Boise Center Aerospace Laboratory.

2. INL Runway: This is a runway owned by the Idaho National Labs (INL). The hyperspectral data was taken using an unmanned aerial vehicle. Jessica Mitchell at INL is the point of contact for this data set. It is a very flat region, but a small LiDAR dataset that was used for testing and prototyping purposes.

### 3.2 Greyscale slice

A user can chose to visualize a single layer of the hyperspectral image stack with the LiDAR data. We perform texture mapping to read in a single image and display it with the LiDAR data. Figure 2 shows an example image with the LiDAR data on top of the hyperspectral slice. This can help a user get an overview of the data and examine the registration of the two datasets. This can also be further augmented with colored LiDAR points based on the corresponding hyperspectral data for those points.

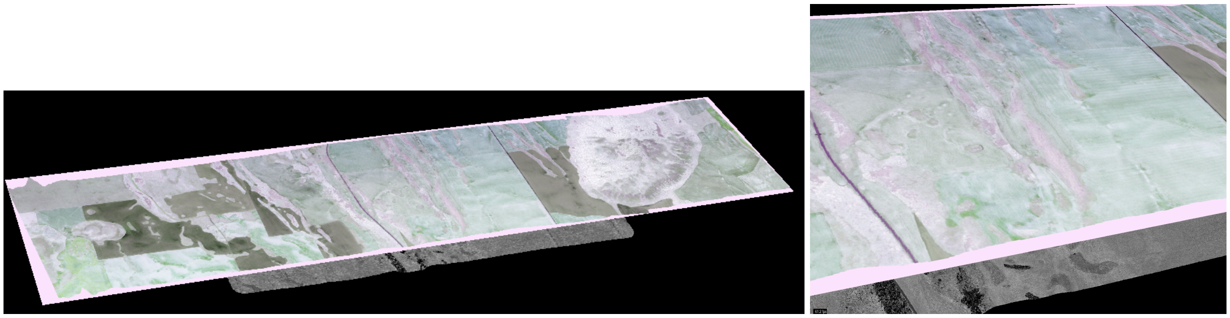

Figure 3: This figure shows a slice-based RGB visualization of the hyperspectral image stack with the LiDAR data below the hyperspectral data. The right image shows a closeup of the hyperspectral data for a particular configuration of the RGB values mapped to levels.

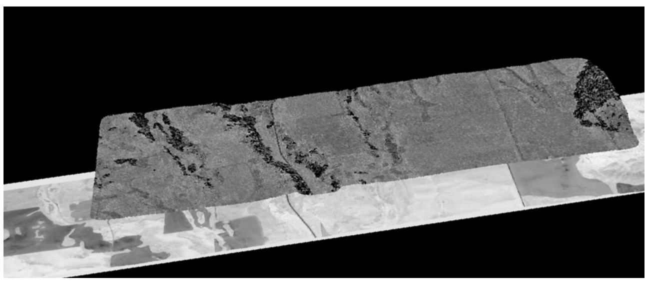

Figure 2: This figure shows a simple slice-based greyscale visualization of a single slice of the hyperspectral stack and the LiDAR data on top of it. A user can user a simple slider bar to change the elevation of the hyperspectral slice.

### 3.3 Colored Slice

Scientists in our group expressed an interest in being able to use the Red, Green and Blue (RGB) channels of an image to encode various levels of hyperspectral data. Based on their training, they are able to visually understand the data better if they are given control over which color in the image slice (R, G, B) maps to which layer in the hyperspectral image stack. Figure 3 shows an example of the slice-based RGB visualization of the hyperspectral imagery with the LiDAR data. In this case, the hyperspectral data is on top of the LiDAR data. We provide the user the ability to specify the band elevation offset which translates the hyperspectral data either over or under the LiDAR data. We provide three sliders (one each for Red, Green and Blue) to allow the user control over which hyperspectral layer/slice is assigned to which color.

### 3.4 Orthogonal Slices

In addition to being able to visualize a single slice, the ability to examine the entire hyperspectral image stack can provide further insight into the entire hyperspectral data. We provide an orthogonal slice view that displays three orthogonal slices that are texture mapped with the hyperspectral data. A user can interactively select the position of the xy-,xz- and yz-planes using three sliders as shown in Figure 4. Here we show that we can link the colormaps of the hyperspectral and LiDAR data to facilitate correlation. Any change to the color map of the hyperspectral data will be simultaneously reflected in the orthogonal slices as well as the LiDAR data.

### 3.5 Volume Rendering

Volume rendering can provide insight into the data by providing a composite view of the hyperspectral image stack. The volume

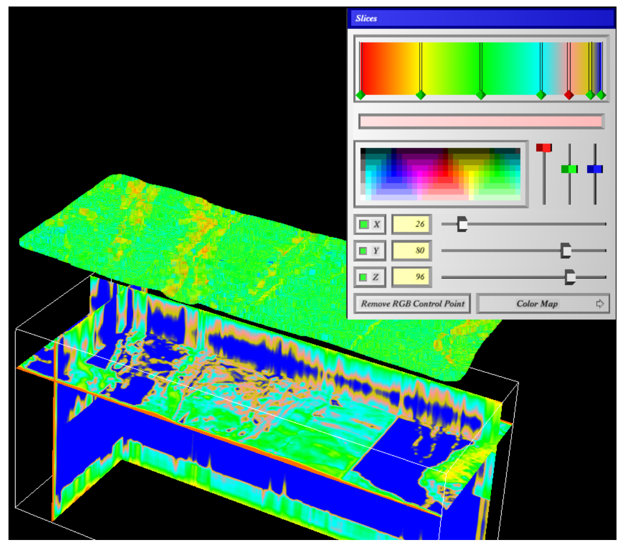


Figure 4: Orthogonal slices display the hyperspectral data. The slice positions can be changed using the slider for each slice. The color map for the LiDAR data and hyperspectral slices can be linked, which helps with correlating locations in the data.

rendering integral is evaluated along the ray as it traverses the hyperspectral stack. The process of assigning colors is based on a user-defined function called the *transfer function*. This function maps the intensity values of the raw data to a color and opacity. Figure 5 shows an example transfer function where the histogram of the hyperspectral stack is shown in the middle window of the 1D Transfer function editor widget. A user can use the control points (shown in blue) to modify the transfer function. Defining an optimal transfer function automatically is extremely hard [3, 5] and finding an optimal transfer function requires tedious manipulation.

We provide the user with the ability to specify a 1D transfer function (as shown in Figure 5) as well as a 2.5D transfer function (Figure 6). 2.5D transfer functions provide an interface to the transfer function space and facilitate the identification of surface boundaries within a volume [14, 15]. Figure 6 shows one such transfer function with the resulting image shown below. In this case, the user is shown a two dimensional histogram in the right window with the gradient on the y-axis and the intensity of the hyperspectral imagery on the x-axis. Identifying regions of high gradient and a known intensity can lead to clean boundaries between surfaces as can be seen in Figure 6.

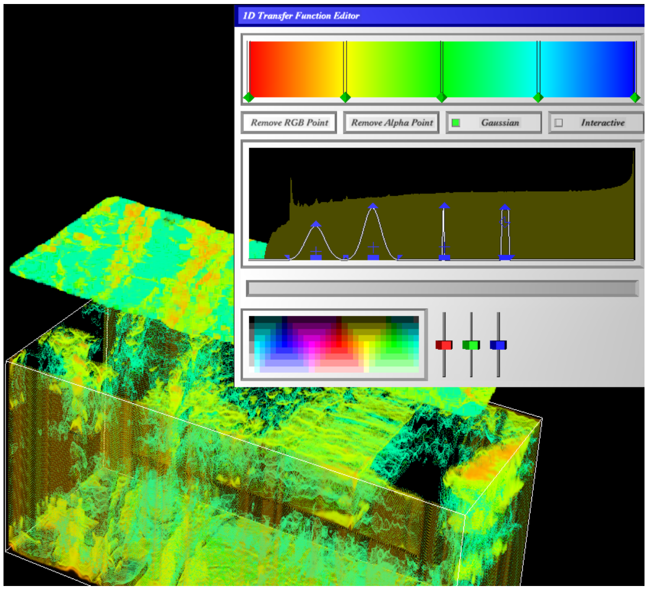


Figure 5: One-dimensional transfer functions map intensity values in the hyperspectral data to color and opacity as specified by the user. The 1D Transfer function editor widget shows the interface that can be used to change the mapping. The blue triangles are the control points that can be changed to vary the transfer function.

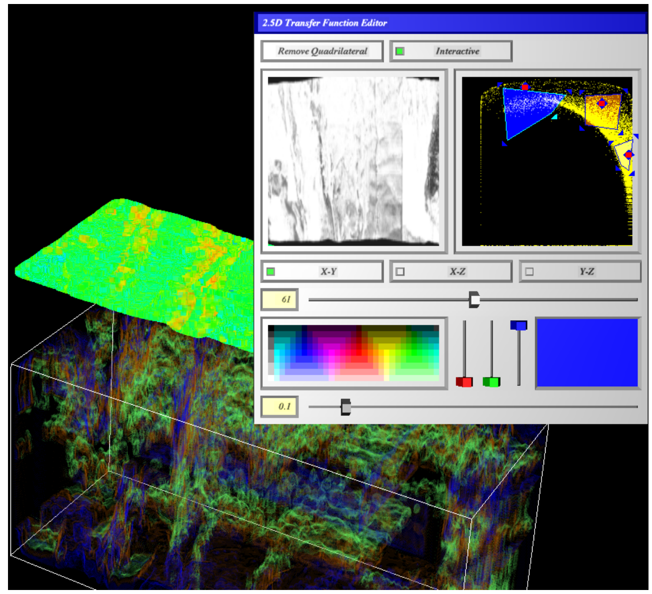


Figure 6: This figure shows a 2.5D transfer function being used along with the corresponding visualization. The 2.5D transfer function has been shown to highlight boundary surfaces in volumetric data [14, 15] and accordingly highlights boundary surfaces in the hyperspectral data. These boundaries offer insights into the properties of the region.

## 4 Implementation Details

RSVP was built on top of the VRUI VR software[21, 18] that is a visualization package designed to create a 3D immersive solution across multiple display types including desktops, IQ Stations, and the CAVE™. The package is written in C++ and has several existing applications built on top of it including LiDAR Viewer, 3D Visualizer, and Toirt-Samhlaigh (Volume Visualizer). These applications perform specific tasks, for example LiDAR Viewer can visualize large amounts of LiDAR data and Toirt-Samhlaigh can perform volume visualization, but none of them contain a mechanism to display both point and raster data in the same scene. In order to provide volume visualization functionality, we adapted the code from Toirt-Samhlaigh to use the built-in widgets for 1D and 2.5D transfer functions.

### 4.1 Performance evaluation

In order to evaluate the ability of RSVP to load reasonable large datasets, we conducted a performance evaluation on the Chinahat dataset. The runway dataset has been collected by INL due to which some of its details cannot be made public. In any case, the Chinahat dataset is much larger and provides some interesting insights into the performance of RSVP. The numbers reported in the table are the frames per second for visualizing the points and the hyperspectral data in the volume visualization mode, since that mode is the most demanding on the system.

As can be seen in the accompanying table, the system performed fairly well with frames per second around 20 with 10x decimation of the data. For no decimation of the LiDAR point cloud (1x), the system struggled considerably and the frame rates dropped below 4 fps, since we load all the data into memory. This affects the loading time too as can be seen in the last column. The numbers for no decimation (1x) with the hyperspectral image stack visualized as a volume in full resolution (1024) have not been reported since the performance was not interactive. One of the optimizations that we are working on right now is to implement an efficient data structure (similar to Kreylos et al. [18]) to load point data on demand rather than keeping it all in memory at once. That will allow a user to visualize both the datasets at the highest resolution.

| Points | | | Volume | FPS | Load Time |
|---|---|---|---|---|---|
| Size | num points | Dec. | Res. | | (in secs) |
| 47MB | 772,249 | 100x | 256 | 70 | 2.27 |
| 470MB | 7,722,411 | 10x | 256 | 26 | 16.29 |
| 4.5GB | 77,224,118 | 1x | 256 | 2.5 | 137.55 |
| 47MB | 772,249 | 100x | 512 | 60 | 3.1 |
| 470MB | 7,722,411 | 10x | 512 | 27 | 16.55 |
| 4.5GB | 77,224,118 | 1x | 512 | 3.6 | 145.96 |
| 47MB | 772,249 | 100x | 1024 | 30 | 5.72 |
| 470MB | 7,722,411 | 10x | 1024 | 19 | 19.1 |

## 5 Discussion and Future Work

RSVP is currently being used in the Boise Center for Aerospace Laboratory as well as the Center for Advanced Modeling and Simulation at the Idaho National Labs. Scientists are finding the RGB slice view and the orthogonal slices to be extremely useful for exploration. The volume rendering views generate visually appealing images, but the transfer function specification seems non intuitive to our users. Researchers in the volume visualization field have identified this problem for almost a decade and it is a well researched topic [24, 5, 3].

Some of the next steps include facilitating fine grained exploration where a user can examine the profile of a single pixel in the hyperspectral image. This would be displayed as a profile of the pixel over all the levels/slices in the hyperspectral data. This would facilitate comparison of various regions by examining their respective profiles. Automatic classification of the LiDAR data based on the hyperspectral data is another feature that we are currently working on. We have also been requested to add a feature fusing other modalities including photos and videos and correlating LiDAR points with structure obtained from motion [16, 28].

## 6 Conclusion

We have presented a visualization platform (RSVP) that facilitates the fusion of data obtained from varied sensors. Both the datasets are automatically registered based on the coordinates in the LiDAR file. Scientists can explore the fused data using a variety of visualization techniques such as a single greyscale slice, colored RGB slice with control over which hyperspectral slice is mapped to which of the three colors (R, G or B), three orthogonal slices that provide a profile view around a specific x, y, z-location as well as a volume rendering of the hyperspectral data. Expert feedback indicates that the ability to explore fused datasets makes it easier to examine regions of interest in an immersive environment. We also found that scientists would like to load larger datasets than can be handled by our system right now and are currently working on optimizing the same.

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