

# A Tri-Space Visualization Interface for Analyzing Time-Varying Multivariate Volume Data

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## Abstract

*The dataset generated by a large-scale numerical simulation may include thousands of timesteps and hundreds of variables describing different aspects of the modeled physical phenomena. In order to analyze and understand such data, scientists need the capability to explore simultaneously in the temporal, spatial, and variable domains of the data. Such capability, however, is not generally provided by conventional visualization tools. This paper presents a new visualization interface addressing this problem. The interface consists of three components which abstracts the complexity of exploring in temporal, variable, and spatial domain, respectively. The first component displays time histograms of the data, helps the user identify timesteps of interest, and also helps specify time-varying features. The second component displays correlations between variables in parallel coordinates and enables the user to verify those correlations and possibly identify unanticipated ones. The third component allows the user to more closely explore and validate the data in spatial domain while rendering multiple variables into a single visualization in a user controllable fashion. Each of these three components is not only an interface but is also the visualization itself, thus enabling efficient screen-space usage. The three components are tightly linked to facilitate tri-space data exploration, which offers scientists new power to study their time-varying, multivariate volume data.*

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Display Algorithm I.3.6 [Computer Graphics]: Interaction techniques I.3.8 [Computer Graphics]: Applications

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## 1. Introduction

In many areas of study, scientists perform large-scale numerical simulations to understand complex phenomena and relations. The output from their simulations is often so voluminous and complex that scientists must rely on advanced visualization tools to interpret the calculated results. Even though many novel visualization techniques have been introduced, an often neglected aspect of these tools are user interfaces. The user interface of a visualization tool can strongly influence the productivity of the user. Furthermore, a carefully designed interface can support and encourage exploration and discovery.

In this paper we present an interface for visualizing time-varying multivariate volume (TVMV) data. In volume rendering, a critical task is to define a set of opacity and color

transfer functions that can best reveal the features of interest in the data. Defining transfer functions for one variable in a steady state data set is already a time-consuming task. A typical TVMV data set found in modern scientific applications can contain over thousands of timesteps and a hundred variables. To understand the spatial and transient relations between these variables and timesteps requires greater control of the way to probe, associate, transform, and animate the data. Conventional interfaces only allow the user to define a single transfer function to visualize one variable at a time, which limits the extent of the exploration and thus prevents the user from obtaining deeper insights in the data.

An ideal user interface for visualizing TVMV data should enable the user to explore not only the spatial and temporal domains but also the variable and rendering parameter space in a tightly coupled fashion. Immediate visual feedback in response to user action is also important for effective data analysis. The basis of our design is the under-

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standing that we cannot directly perceive structures and patterns beyond 3D. We can, however, achieve that goal by visually linking pieces of information perceived in different lower-dimensional spaces to understand relations in a higher-dimensional space.

Our TVMV visualization interface consists of three components which abstracts the complexity of exploring in different spaces of the data and visualization parameters. Most importantly, it is not only an interface but also the visualization itself. The first component displays the time histograms [AFM06] of the data. A time histogram shows how the distribution of data values changes over the whole time sequence and can thus help the user to identify timesteps of interest and to specify time-varying features. The second component attempts to display the potential correlation between each pair of variables in parallel coordinates for a selected timestep. By examining different pairs of variables the user can often identify features of interest based on the correlations observed. The third component is a hardware accelerated volume renderer enhanced with the capability to render multiple variables into a single visualization in a user controllable fashion. Such simultaneous visualization of multiple scalar quantities allows the user to more closely explore and validate their simulations from the parallel-coordinate space to the 3D physical space. These three components are tightly cross linked to facilitate tri-space data exploration, offering scientists new power to study their TVMV data.

We demonstrate the effectiveness of this interface with case studies using a turbulent combustion dataset and a hurricane Isabel dataset. It is clear from these case studies that this new interface makes it easier for the scientists to specify features of interest that would be previously tedious, if not impossible, to uncover. It also allows the scientists to freely explore data previously unavailable, which could lead to new discoveries.

## 2. Related Work

Time-varying data visualization presents many unique challenges from data management, feature extraction, rendering, and interaction to interpretation. A survey of early works on time-varying data visualization is given in [Ma03]. Our work places a focus on making a user interface for feature identification and tracking. We also take into account scientists' need to look at multiple variables simultaneously. Several previous research results are worth discussing here.

### 2.1. Multivariate Data

Image Surfer [JPR\*04] is a tool for exploring correlations between two 3D scalar fields. It is specially designed to find the location of a protein embedded in the plasma membrane of neurons (nerve cells). Image Surfer enables scientists to analyze relationships between multiple data sets obtained from confocal microscopy by providing a 3D surface view,

the height field on a 2D slice, and a 1D plot. As the user understands global aspects of the data via the 3D surface view, the dimension is reduced one by one for further analysis of the data. In order to apply this technique to TVMV data, a global view also along the time dimension needs to be introduced.

WEAVE is an environment for creating interactive visualization applications [GRW\*00]. WEAVE provides transparent linking between custom 3D visualizations and multi-dimensional statistical representations. It allows interactive color brushing between all visualizations. Sauber et al. [STS06] introduce the Multifield-Graph, a node-link representation of the different aspects of the correlation information derived from a multivariate dataset, as a guide to select and visualize the most prominent correlations. However, both WEAVE and Multi-field Graph have no support for visualizing time-varying volume data.

Kettner et al. [KRS03] presents an interface for visualizing time-varying iso-surfaces and contour spectra. In their system, a specific property of the iso-surface is illustrated in a 2D display called the control plane, which shows summary information of the selected iso-surface over the whole time sequence. The information includes the number of connected components, number of tunnels, and distribution characteristics of the values of other data sets. Mouse clicking on the control plane triggers the display of the corresponding pre-rendered iso-surface in a small preview window.

Tzeng et al. [TM05] introduce a painting user interface for performing feature extraction and tracking of time-varying flow data. The complexity of defining a feature of interest in a higher dimensional space is significantly reduced by using a machine learning engine. The painting user interface is intuitive to the user since it allows the user to operate directly on the volume data by using brushing.

Woodring and Shen [WS06] make comparative visualization of multivariate time-varying volume data using set operators along with a spreadsheet-like and volume tree interface. However, without knowing which operators to use, certain correlations cannot be uncovered.

As opposed to the graphical interface approach introduced so far, language-based interfaces [MH99, MIA\*04] are also viable. While most visualization techniques rely on some data-to-visual mappings specified graphically to generate an image, a language-based interface expresses these mappings via mathematical formula or queries that can be directly applied to the data, thus allowing domain scientists to conduct quantitative analysis in a more familiar environment. However, this strategy is effective only if the user knows what to analyze and if those tasks can be expressed in a language.

Our previous work [AMCH07] presents a case study on visualizing multivariate volume data obtained from a turbulent combustion simulation. Several rendering techniques to

enhance the perception of spatial correlations between variables are introduced. The techniques includes data fusion, motion based enhancement, interactive cutting and illustrative rendering. The work also uses parallel coordinates and time histograms to show correlations between variables. In this paper, we use the fusion technique to simultaneously visualize multiple variables. The parallel coordinates and time histograms are now tightly linked with brushing interaction in multivariate and temporal views of the new interface.

## 2.2. Time Histograms

Kosara et al. [KBH04] introduce time histogram, which is a 2D plot of data occurrence over time. A time histogram is quite effective as a global view of time-varying data. Even though it can only display a limited aspect of the data, it has been shown to be quite helpful in visualizing time-varying data. Our interface displays time histograms to assist the user in identifying features of interest and selecting key timesteps. The user can operate directly on histograms to isolate features. As demonstrated in our previous work [AFM06], the time histogram can help classify temporal features and characterize time series leading to data reduction in the time dimension.

Doleisch et al. [DMG\*04] introduce a smooth brushing interface for specifying the features of interest in multivariate volume data. Their interface consists of a 2D scatter plot and a 3D visualization view. The scatter plot shows the correlation between any two statistical features from different variables. The opacity transfer function is defined by positioning two square-frames on the plot, which defines the non-discrete degree of interest (DOI). They state that DOI is suitable for flow simulation data, which does not have sharp boundaries of flow features. For time-varying data exploration, their system also shows a time histogram revealing some time-dependent property of the data. However, there is no system-supported means to further utilize the time histogram.

## 2.3. Parallel Coordinates

One section of our visualization interface uses Parallel Coordinates (PC), a technique created to visualize multivariate data [Ins85, ID90]. Its basic form is a 2D display plotting data using parallel axes, one for each variable. PC generally can provide a good overview of the correlation among multivariate data but it has limitations. Using it to visualize a large data set often suffers from over-plotting, resulting in an image that is too cluttered to show trends or structures. In order to solve this problem, Johansson et al. [JLJC05] propose to display the clustered multivariate data instead, and use high-precision textures to better superimpose layers of structures. Novotny and Hauser [NH06] also address this over-plotting problem using a focus-context approach. They introduce a scheme to offer context visualization at several levels of abstraction by mapping data item pairs to 2D histogram space.

In this space, outliers and trends are detected separately and they are shown separately on top of the focused data items in the parallel coordinate space. Bendix et al. [BKH05] introduce Parallel Sets that adopt the layout of PCs, but substitutes the individual data points by a frequency-based representation for categorical data variables, since frequency data is best represented by areas instead of individual data points. Similar to this concept, the axis of PC is used to map additional information in our work.

Parallel coordinates has also been utilized in making volume visualization. Tory et al. [TPM05] designed a PC based interface that shows the process of volume visualization. Various parameters, including view position, orientation, dataset selection, transfer function and several others are mapped to each axis. The work more relevant to ours is [LM04], which uses a PC interface to reveal the correlation between two scalar values along the gradient direction for controlling lighting in volume rendering. The interface consists of a pair of horizontally aligned axes for two scalar quantities and a 1D transfer function for each axis. Our interface design is intended to be more general, allowing any types and numbers of volume properties to be displayed in parallel coordinates.

## 3. A User Interface for TVMV Data Visualization

Our design objective of a user interface (UI) for visualizing TVMV data is to make the UI a part of the visualization that provides the user many different views of the data in a user controlled fashion. That is, the UI is not only used as a parameter specification tool but also is the visualization itself. In this way, the amount of information that is presented in a confined screen space is maximized. As shown in Figure 3, there are three main components in our UI, including temporal view, multivariate view, and spatial view which enable the exploration of the data in temporal, variable and spatial domains, respectively. These three components are tightly coupled to help the user better relate and verify the features of interest in different spaces. Each component is described in this section.

### 3.1. Temporal View

A conventional histogram plots scalar value versus its frequency of occurrence. For a time-varying volume data set we can compute a conventional 1D histogram for each timestep, and then compose and concatenate all these 1D histograms together. The result is a time histogram which gives frequency of occurrence for each value and time. It contains a wealth of information about the entire time series. For one, it provides a concise statistical overview of the data. Second, it offers a global context within which temporal features (i.e. events) can be distinguished. Our UI adopts and extends time histogram to support TVMV data visualization. In the temporal view, several time histograms are shown side by side

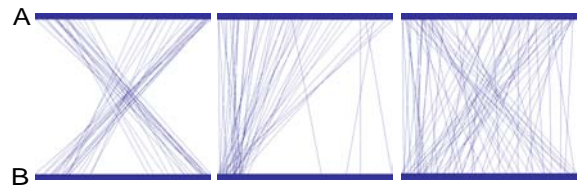
(see Figure 3) depicting the correlations between variables. The user can select any variable and a type of data; either the original voxel value or derived quantities such as spatial gradient, temporal gradient and curvature. In this way, the temporal view facilitates the process of finding timesteps of interest and classifying time-varying data since the correlation information can be obtained by comparing several different time histograms. Defining a transfer function for the whole time sequence is a challenging task [JM01]. However, the classification of time-varying data can be efficiently performed for each variable using time histograms [AFM06]. The temporal TF widget can be defined either manually with mouse interaction or semi-automatically by clicking the pre-segmented region in the time histogram.

In our previous work [AFM06], the entire voxels of the input volume data is used to compute frequency counts leading to a time histogram. Thus, certain subtle features may be obscured by other data values. To solve this problem, we design our system to compute frequency counts for specific voxels or voxel subset which results in partial time-histogram. The selection of such voxels is performed in the multivariate view.

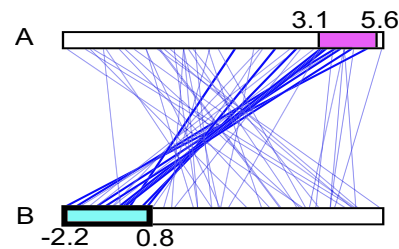
### 3.2. Multivariate View

To possibly perceive the potential relationship between multiple variables, we have developed an interface based on parallel coordinates, demonstrating its expressive power in multivariate feature extraction. Our interface design uses a horizontal layout for the parallel coordinates to align with the time histograms. Once the data properties are selected for the axes, lines are drawn between pairs of axes where each line corresponds to a voxel.

One problem with parallel coordinates is that when the number of data items is large, the lines drawn opaque can result in over-plotting. This problem can be alleviated by pre-clustering the data and using semitransparent lines to bring out the cluster features [FWR99, JLJC05] or using focus+context approach [NH06] as described in the related work section. By observing line clusters between two neighboring axes of parallel coordinates, the correlation between the corresponding variables can be detected. Some typical patterns are shown in Figure 1. Our interface allows the user to define transfer functions for volume rendering directly on the axes of parallel coordinates. This is performed by defining a rectangular widget, which is referred to as TF widget, on the axes via mouse interactions. Once the TF widget is defined, the user is allowed to edit the opacity transfer function within the rectangle in the separate region in our UI. TF widgets are colored based on the color transfer function as shown in Figure 2. TF widgets are interactively movable and resizable. The change made in the widget updates the volume rendering in the spatial view. Thus, an interactive rendering in the spatial view is quite important since immediate visual feedback facilitate the overall visual analy-



**Figure 1:** Typical line patterns that could be shown in parallel coordinates. The left-most image shows negative correlations between A and B. The middle image shows a strong correlation between A and the low-value range of B. The right-most image shows no obvious correlation between A and B.



**Figure 2:** The magenta and cyan TF widgets are defined to capture the correlation between high values in A and low values in B, respectively. The cyan TF widget at the bottom is used as a selection tool. The data values at the edge of TF widgets are also shown.

sis process. The TF widget also functions as a brushing tool to highlight certain voxels or a voxel subset. As shown in Figure 2, the TF widget for variable B is used as a brushing tool, thus highlighting all the lines within the range of that widget. The user can choose if each TF widget is used as a brushing tool or not. When more than one TF widget are used as a brushing tool for more than two axes, either AND or OR operation is performed to capture a voxel subset. An interactive brushing scheme is quite important to give a user immediate feedback as the TF widget is moved or resized.

This multivariate view effectively guides the user to select the correlated features between variables and specify features to be visualized in spatial view.

### 3.3. Spatial View

Whereas the temporal and multivariate views show statistical features of the input data, volume rendering provides the user the most direct and intuitive view of the data. We designed the spatial view to show volume rendering of multivariate data. The challenge is how to enhance the perception of the spatial relationships between two or more variables. We adopt the volume fusing and rendering approach described in [AMCH07]. One requirement is that the spatial



relationship between different variables in the image must be clear. Another is that a user must receive immediate visual feedback as the rendering parameters or transfer functions change.

### 3.4. Linking between Three Views

One of the essential aspects of our interface is that the three views are tightly linked to provide deeper insight of the data during the user interaction with one of the views. One effective linking feature between the temporal and multivariate views is the propagation of voxel subset information specified in multivariate view to temporal view. Once the highlight widgets are defined in multivariate view, the histogram of the voxel subset is computed for each timestep revealing the temporal trend of the voxel subset. Another feature is the linking between TF widget in multivariate and temporal view. As the user defines a temporal TF widget in temporal view, the corresponding TF widget will be shown in multivariate view. Resizing or translating a TF widget updates the corresponding TF widget. Every time a TF widget or a temporal TF widget is moved or resized, the volume rendering in the spatial view is updated.

## 4. Case Studies

In order to demonstrate the usefulness of the new user interface, we have conducted two case studies using a combustion simulation data set and a hurricane simulation data set. These studies show how this interface helps identify and specify features in spatial, variable and temporal domains. The combustion dataset consists of 122 timesteps and 5 variables, where each volume is of size 480x720x120. The hurricane dataset consists of 48 timesteps and 12 variables, where each volume is of size 500x500x100. Hardware accelerated slice-based volume rendering is used for the spatial view. In order to keep high interactivity in the multivariate view, a downsampled volume is used to draw correlation lines in parallel coordinates.

### 4.1. Case I: Visualizing A Combustion Simulation

The goal of this case study is to verify the correlation between three variables from the combustion dataset. The specific task is to see if scalar dissipation ( $\chi$ ) and OH radical ( $OH$ ) spatially overlaps or not near the stoichiometric mixture fraction ( $mixfrac$ ) iso-surface with iso-value=0.42. The  $\chi$  and  $OH$  should be in the higher value range.

Figure 3 (a) shows the multivariate view of the scalars  $mixfrac$ ,  $\chi$  and  $OH$ , which are mapped to the three axes from bottom to top, respectively. An important functionality of this view is the ability to specify a subset of the data to highlight. This is accomplished by selecting a range along one axis first, and refine as needed by selecting along other axes. The lines originating from the selected data points are

highlighted, as shown in Figure 3. The semi-transparent gray lines between the three axes correspond to the entire set of voxels, and the blue lines link the selected voxel subset. To examine the extent  $\chi$  and  $OH$  overlap near  $mixfrac \approx 0.42$ , at a particular time step, we first select a small range of  $mixfrac$  values (in blue) in the neighborhood of 0.42, and then we select  $\chi$  values (in yellow). By observing the data range on the  $OH$  axis where these blue lines fall, we are also hinted where to position the TF widget. The important data range here is high  $OH$  where the blue lines do not fall in. For instance, this non-overlapping range for timestep 39 is from 0.0013 to 0.003. After obtaining this non-overlapping range, we can define the red TF widget on the  $OH$  axis to verify in the spatial view if  $OH$  and  $\chi$  do not spatially overlap. The spatial view in Figure 3 (c) shows the simultaneous volume rendering of three variables. We can verify the spatial correlation and determine if the TF widget should be moved or resized.

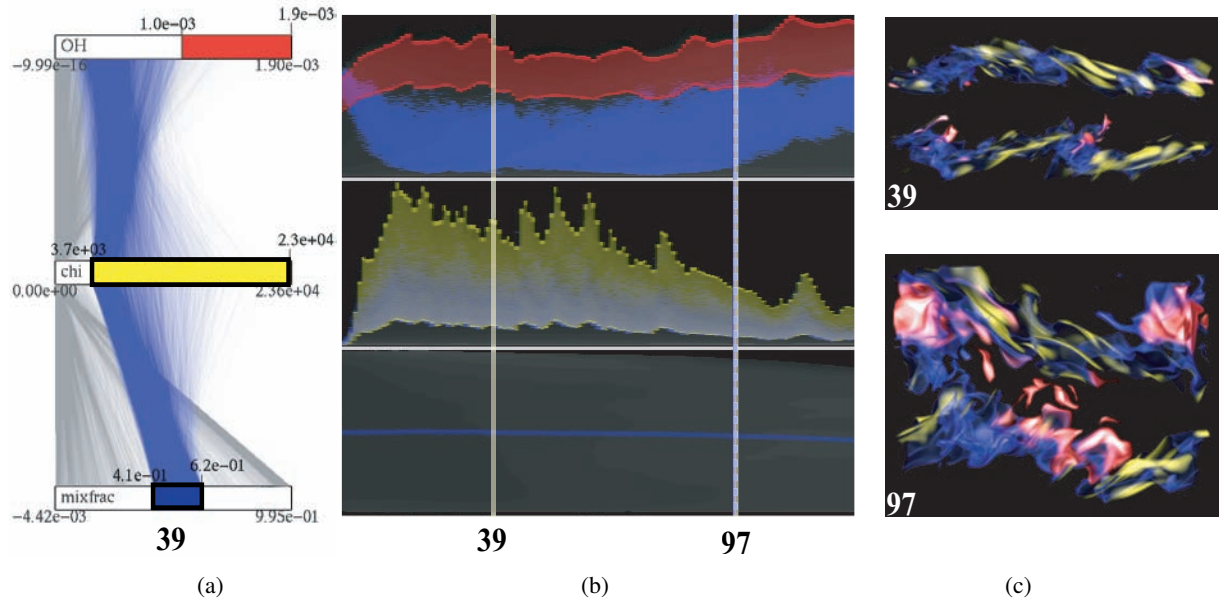
The steps we have taken so far do not guarantee the non-overlapping situation holds for a time period. In fact, the temporal view in Figure 3 (b) reveals the interval over which  $\chi$  and  $OH$  do not overlap. However, this non-overlapping range may vary over time and the temporal view allows us to quickly determine the temporal behavior of the flow over a particular period as shown in (b), where the highlighted blue lines in (a) appear as a blue band. The temporal TF widget in this case may be used to define the transfer function for  $OH$  in a way such that there is no overlap between the red band and blue band in (b). This capability is powerful, especially when the number of timestep is large. Finally, we can also check the evolving correlation between different variables in the spatial domain with the spatial view by stepping through the time steps.

In this case study, the simultaneous visualizations of mixture fraction, portraying the flame surface, was visualized together with other variables such as  $OH$ , representing the mass fraction of the hydroxyl radical, and  $\chi$ , representing a local mixing rate. While in isolation these quantities are largely meaningless, together it is possible to understand how the mixing is interacting with the reaction and to identify the actively burning flame surface. The interface, which provides multiple views and interactive cross exploration of the data, is proving useful to develop qualitative understanding, and it is expected the interface will also prove very useful to guide further quantitative analysis.

### 4.2. Case II: Visualizing A Hurricane Simulation

The goal of this case study is to find correlations between cloud moisture mixing ratio ( $cloud$ ), magnitude of wind velocity ( $wind\ speed$ ), water vapor mixing ratio ( $vapor$ ), and  $pressure$ . Two insights extracted from hurricane datasets through our UI are explained below.

The first insight is obtained from a spatial correlation



**Figure 3:** Visualization of the combustion dataset to find negative spatial correlation between variables  $\chi$  and OH near the iso-surface of mixfrac over time. Three components in our UI are shown including the multivariate view for timestep 29 (a), the temporal view for three variables where  $x$  and  $y$  axes correspond to timestep and data value, respectively (b), and the spatial views for timestep 2 and 29 (c). In the multivariate view, the TF widgets of  $\chi$  and mixfrac are used as the brushing tool, thus highlighting voxels of yellow thin flow features shown in the spatial view near the blue iso-surface. The temporal view shows the histogram of the voxels over time in blue as well as the temporal transfer functions.

between wind speed, vapor, and pressure. Figure 4 (a) shows that the high vapor region is correlated to both the low wind speed region and high pressure region. This is achieved by highlighting the voxel subset as navy-blue lines using the red TF widget for vapor as a brushing tool. Thus, all the voxels of vapor in the range  $[0.18, 0.024]$  are highlighted. Even though the temporal resolution of this data set limits the quality of temporal information on the time-histogram, we can observe the same correlation in the entire 48 timesteps as shown in Figure 4 (b). This result corresponds to the fact that the high vapor region is spatially located above the sea surface where pressure is high and wind speed is low. It is important to note that the insight cannot be obtained without the parallel coordinate based interface tightly linked to time histograms. With this interface, the correlations of two variables pairs are simultaneously visualized and such correlations are highlighted in time histogram of pressure and wind speed, where the highlighted region is specified by vapor. Once this global trend is discovered in the temporal view, the temporal transfer function may be used to capture the trend directly on the time histogram. In Figure 4, light blue, yellow, red and blue temporal transfer functions are defined for cloud, wind speed, vapor and pressure, respectively. We can always go back to the multivariate view to refine the transfer functions and explore the data in the spatial view.

The second insight gained from Figure 4 is how the hurricane gains and loses its power over time. By observing the histogram of wind speed and pressure in temporal view along with the cloud structure of hurricane in spatial view, it is found that wind speed of the hurricane fluctuates overtime while pressure in the eye of the hurricane keeps decreasing until it lands on the ground surface. The procedure to derive this observation through time-histograms is explained as follows. The black region in time-histogram corresponds to the region of zero or almost zero frequency counts. Thus, the boundary between black and light-gray area in the time-histogram indicates the maximum data value for each timestep. By observing time-histogram of wind speed and pressure, it is found that the maximum value of wind speed increases rapidly from timestep 1 to 7 whereas the minimum value of pressure decreases. From the spatial view, we can confirm that the cloud concentrated in a particular region starts to spread over a wider geographical domain from timestep 1 to 7. We can also confirm that the low pressure region exists in the eye of hurricane. Thus, the characteristics of hurricane when it is gaining power are revealed during this timestep period. After timestep 7, pressure keeps decreasing until timestep 37 whereas wind speed fluctuates but maintains high value. After timestep 37, the minimum pressure value starts to increase whereas the maximum wind speed starts to decrease. In the spatial view, timestep

37 corresponds to the timing when the hurricane approaches the ground surface. Hence, the data characteristics of hurricane when it loses power are discovered.

This case study along with the first one demonstrate several unique features of our visualization interface and its benefits which are summarized as follows. Firstly, the parallel coordinate based interface in the multivariate view helps the user gain quantitative information such as data ranges of interest. Secondly, the temporal view helps the user to find interesting statistical temporal features covering all the voxels or its subset. Thirdly, while observing the correlation information presented in the multivariate and temporal views, we can define the features to be visualized in the spatial view.

## 5. Conclusion

The design of the UI for a visualization system is as important as that of the visual transformations and rendering techniques. A carefully designed interface can significantly increase the performance of the user on complex visual analysis tasks. We present a UI for visualizing time-varying multivariate volume data. This interface is composed of three tightly coupled views characterizing the data in different spaces. Our case studies show that this interface gives the user both broader and deeper views of the data as well as more expressive power in specifying her intent. In particular, the ability to detect and capture the correlation in both multivariate and temporal view is shown useful using two different datasets. The combustion simulation scientists actually participated in the first case study and found the UI very desirable. We were able to extract and display a fairly complex feature that they previously could not see.

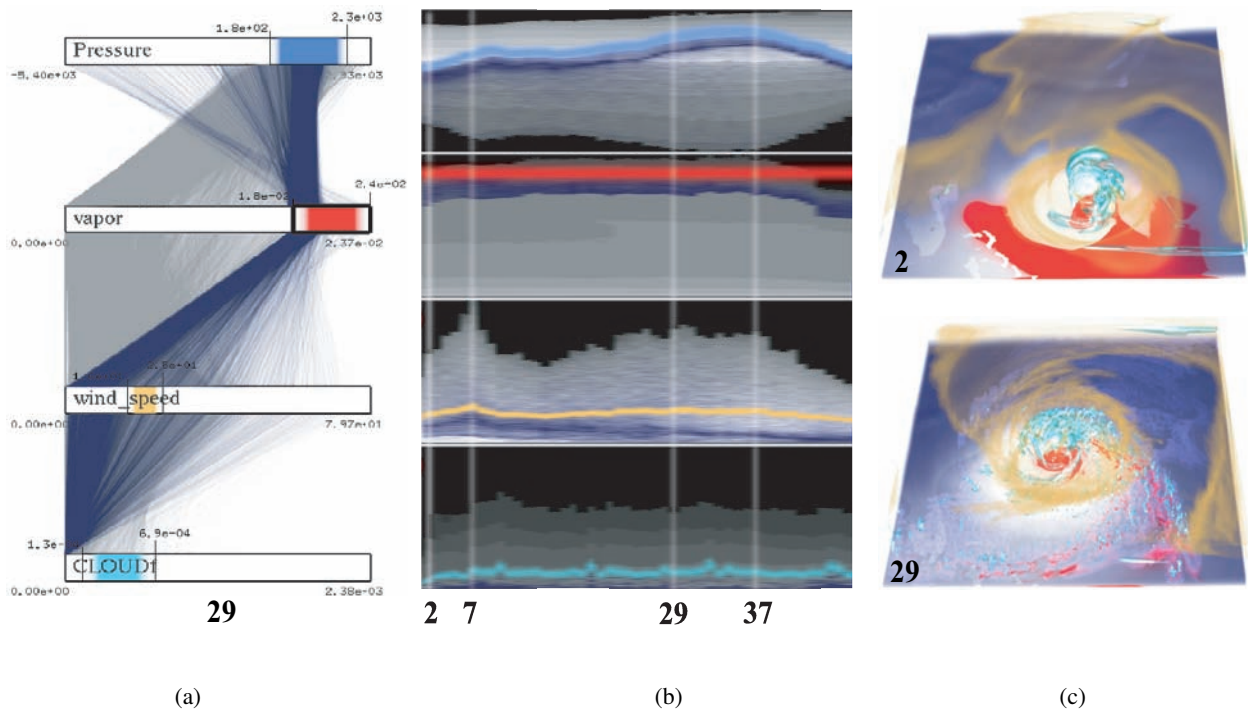
For future work, alternative representation to show the temporal correlation between variables may be desired rather than the side-by-side comparison in our current design as the number of variables to be compared increases. Also, the utilization of several different statistical properties in time histogram or parallel coordinates should be explored. Finally, we anticipate to obtain more feedbacks from the scientists after they begin to routinely use this interface and the visualization system, and we can refine our design accordingly.

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**Figure 4:** Exploration of the hurricane dataset to find correlation between cloud, wind speed, vapor and pressure. Three components in our UI are shown including the multivariate view for timestep 29 (a), the temporal view for the four variables (b), and the spatial views for timestep 2 and 29. The red TF widget for vapor is used as a brushing tool so the voxels of high vapor are highlighted in navy-blue in the multivariate and temporal views.

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