Knowledge-Assisted Visualization of Turbulent Combustion Simulations

Chaoli Wang Hongfeng Yu Kwan-Liu Ma

University of California, Davis

ABSTRACT

In this paper, we present a knowledge-assisted approach for studying turbulent combustion simulation data. To understand the dynamic mechanisms of extinction and reignition in turbulent flames, scientists need to validate known relationships and reveal hidden ones among multiple variables. Based on the domain knowledge and questions posted by the scientists, we have designed an algorithm that helps scientists examine complex variable relationships in turbulent combustion simulations.

1 INTRODUCTION

Combustion accounts for 85% of the energy production in the United States [2]. A deep understanding of the basic phenomena of reacting flows in turbulent combustion processes is essential to the development of next generation highly efficient combustion devices that provide a more secure, environmentally sound energy infrastructure. Leveraging the power of high-performance supercomputers and the advancement of numerical algorithms, scientists at Sandia National Laboratories are able to perform three-dimensional fully-resolved direct numerical simulation (DNS) of turbulent combustion [2]. With full access to the spatially and temporally resolved fields, DNS plays a major role in the development of fundamental understanding of the micro-physics of turbulence-chemistry interactions.

Nowadays, a typical turbulent flow simulation may produce data sets that contain several hundred million voxels, hundreds of time steps, and tens of variables. A subset of the time-varying, multivariate combustion data set that scientists provided to us has a spatial dimension of $800 \times 686 \times 215$, a total of 53 time steps, and four variables. These variables are scalar dissipation rate (chi), stoichiometric mixture fraction ($mixfrac$), hydroperoxy radical (HO_2), and hydroxyl radical (OH). The total size of this subset of data is already about 93GB.

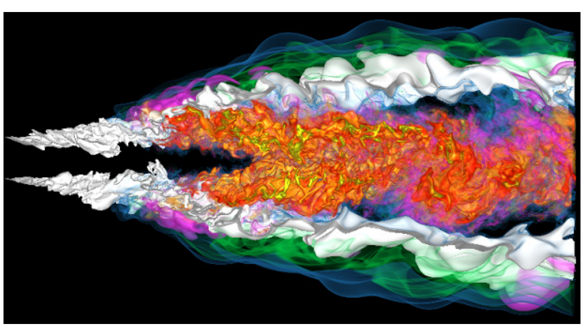


Figure 1: The traditional way of mixed rendering the $mixfrac$ (at the isovalue of 0.2) and HO_2 variables. Note that the distribution of HO_2 values close to the surface is unclear in this rendering.

In a desired visualization, the scientific interest is two-fold: the overall structure of the jet flame, and the lifted flame base region to understand what is stabilizing the lifted flame. More specifically, the visualization task is to show the mixture fraction ($mixfrac = 0.2$) with the HO_2 and OH plots. It would also be useful to bring out more the lower values of HO_2 and OH.

2 CHALLENGES

There are several challenges for this specific visualization task. First of all, although scientists know exactly the mixture fraction surface of interest, they do not know what the corresponding data ranges for HO_2 and OH at positions close to the $mixfrac$ surface are. Second, it is possible to find out the data ranges for HO_2 and OH near the $mixfrac$ surface using a trail-and-error approach or an enhanced interface [1]. However, we may also bring out visualization content that does not intersect with the $mixfrac$ surface of interest if the transfer function we use is solely based on the data value. As scientists are interested in investigating how HO_2 and OH intersect with the mixture fraction surface, anything that is not close to the given isosurface should potentially be suppressed in the rendering in order to avoid cluttering or confusion in their understanding. Finally, there is a great need to provide scientists with the flexibility to choose the amount of information displayed in the rendering. However, the traditional way of multivariate rendering does not support this capability. For example, Figure 1 shows a typical mixed rendering of the $mixfrac$ and HO_2 variables. Note that while the image is visually appealing, there is no control over the HO_2 variable shown with respect to the given isosurface. Moreover, we are not able to observe the relationships between these two variables close to the surface.

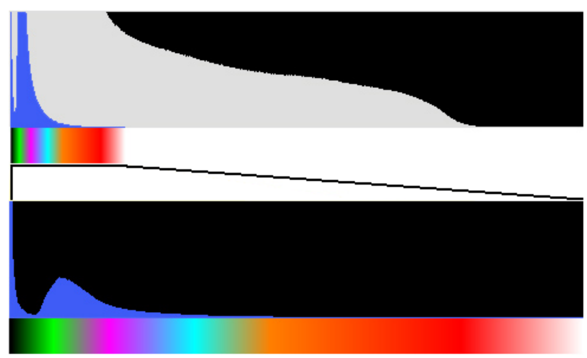
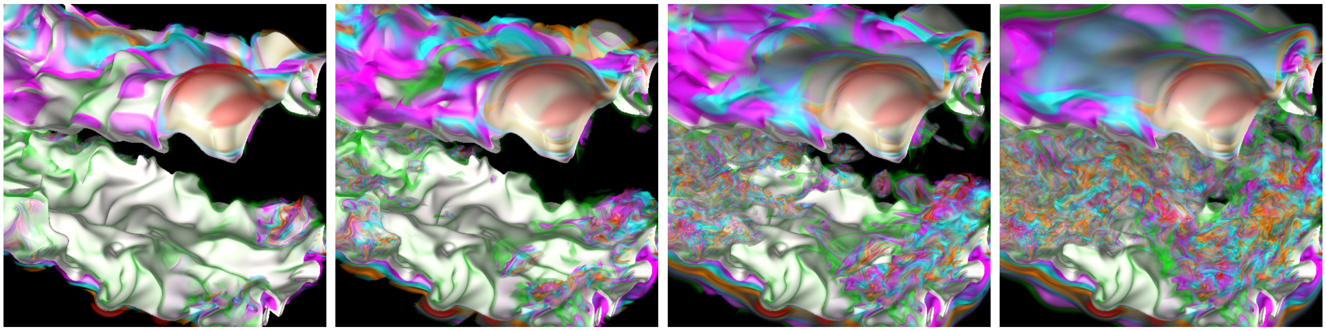


Figure 2: Top: the original histogram (gray) and the partial histogram (blue) of the HO_2 variable. Bottom: the partial histogram is scaled for a more convenient transfer function specification.

3 OUR APPROACH

We propose the following algorithm to study the relationships between the $mixfrac$ surface and the HO_2 or OH variable in the turbulent combustion simulations:

1. Scan the volume once and mark all the voxels in the volume that intersect with the $mixfrac$ surface at the given isovalue. We call these voxels the *core voxels*.
2. Create a *distance volume* with initial voxel values of all D, where D is the maximum distance of any voxel in the volume to the given isosurface. Assign a voxel with 0 if it is a



(a) $d = 0.02$ (b) $d = 0.05$ (c) $d = 0.10$ (d) $d = 0.20$

Figure 3: Our new way of rendering the $mixfrac$ surface (at the isovalue of 0.2) and the HO_2 variable. (a)-(d) are four zoom-in images with different distance thresholds. Scientists can clearly observe the interacting relationships between these two variables close to the surface.

core voxel; otherwise, assign the voxel with its distance to the nearest core voxel.

3. Calculate the importance value for each voxel using a linear or Gaussian function with a user-specified distance threshold d (only voxels with their respective distance values less than d are considered; otherwise, their importance values are 0). We call these voxels that have importance values within $(0, 1)$ the *neighboring voxels*.
4. Plot the *partial histogram* of another variable (HO_2 or OH) using the core and neighboring voxels (only these voxels have non-zero importance values). The importance values are used for the histogram bin count (for example, 1 counts for one and 0.5 counts for half).
5. In the plotted partial histogram, the regions with higher histogram bin counts are the ranges of interest (i.e., intersecting with the given $mixfrac$ isosurface) and should be highlighted in the visualization. Use this derived knowledge to specify the transfer function for the variable (HO_2 or OH).
6. The $mixfrac$ surface is rendered as an isosurface with the other variable (HO_2 or OH) rendered using volume rendering to show the relationships between the two variables at the given surface. The importance values are used to modulate the opacity values of HO_2 or OH in the rendering.

Note that the distance volume is calculated once and all the distance values are normalized to $[0, 1]$. This distance volume can be computed as a preprocessing step if the surface of interest (i.e., the isovalue) is known in advance. At runtime, the distance volume is used to update the importance values dynamically when the user changes the distance threshold.

4 Results and Discussion

Figure 2 shows the original, full histogram and the partial histogram of the HO_2 variable. As we can see, using the partial histogram, we are able to distinguish the data ranges of HO_2 that are near the $mixfrac$ isosurface from the original histogram. Typically, the partial histogram may only occupy fairly narrow ranges with respect to the original histogram. Therefore, we allow the users to scale the partial histogram to bring out more the lower values for the specification of the transfer function.

Figure 3 shows four images of rendering the $mixfrac$ surface and the HO_2 variable with different distance thresholds. The distance threshold d is controlled by the user at runtime and interactive rendering is achieved using a GPU-based raycaster. Using our approach, scientists are able to observe the relationships between the $mixfrac$ surface and the HO_2 variable in an effective manner.

Our approach computes the distance volume in relation to a given isosurface, which is similar to the distance field representation [3]. On the other hand, our approach resembles the importance-driven volume rendering work by Viola et al. [4]; however, in our case, the importance value is inversely proportional to the distance to the given isosurface. In the context of multivariate volume visualization, our algorithm is new: it combines the ideas of distance field and importance-driven visualization and can be used to solve the specific visualization task effectively.

5 Conclusion and Future Work

We have presented a study on variable relationships in turbulent combustion simulations. Our solution is able to assist scientists in analyzing the relationships between multiple variables by controlling the amount of content displayed around the surface of interest. The contribution of this work is that we utilize limited domain knowledge (e.g., the isovalue) to derive new knowledge (i.e., the distance volume and the partial histogram) that can be utilized to solve specific scientific questions via visualization.

In our method, the distance volume has the same size as the original volume. For large volume visualization, it may consume a large amount of memory and drop the overall rendering performance. This is more critical for time-varying data visualization, since the isosurface changes over time and the distance volume needs update accordingly. We will investigate the possibility of compressing the distance volume to improve the performance. A solution that takes into account the temporal coherence of the isosurface is necessary. In the future, we will also consider multivariate data encoding that incorporates both the domain knowledge and our derived knowledge into compression for feature-preserved data reduction.

Acknowledgements

We would like to thank Jacqueline H. Chen at Sandia National Laboratories for providing the data set and sharing her knowledge.

References

[1] H. Akiba and K.-L. Ma. A Tri-Space Visualization Interface for Analyzing Time-Varying Multivariate Volume Data. In *Proc. Eurographics/IEEE VGTC Symposium on Visualization 2007*, pages 115–122, 2007.

[2] E. R. Hawkes, R. Sankaran, J. C. Sutherland, and J. H. Chen. Direct Numerical Simulation of Turbulent Combustion: Fundamental Insights Towards Predictive Models. *Journal of Physics: Conference Series (Proc. DOE SciDAC 2005 Conf.)*, 16:65–79, 2005.

[3] M. W. Jones, J. A. Bærentzen, and M. Srámek. 3D Distance Fields: A Survey of Techniques and Applications. *IEEE Transactions on Visualization and Computer Graphics*, 12(4):581–599, 2006.

[4] I. Viola, A. Kanitsar, and M. E. Gröller. Importance-Driven Volume Rendering. In *Proc. IEEE Visualization 2004*, pages 139–145, 2004.