Visual Informatics 4 (2020) 63–68

Contents lists available at ScienceDirect

Visual Informatics

journal homepage: www.elsevier.com/locate/visinf

Visualization Laboratory at University of Notre Dame

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ARTICLE INFO

Article history:
Available online 11 September 2020

ABSTRACT

This article introduces the Visualization Laboratory at the Department of Computer Science & Engineering, the University of Notre Dame, including the lab's overview, current research directions, facilities, and international collaborations.

1. Overview

Located in Northern Indiana, the University of Notre Dame was founded in 1842 by Rev. Edward Sorin. Over the past 175 years, Notre Dame has become one of the premier universities in the United States. The university is well known for its Catholic identity, scenic setting, football program, undergraduate education, and alumni network. At Notre Dame's Department of Computer Science & Engineering, the Visualization Laboratory (VisLab) was established by Prof. Chaoli Wang in 2014. The VisLab is at the forefront of visualization research. According to CSRankings (Anon, 2020a), Notre Dame ranks among the top 20 institutions in the United States based on the IEEE VIS conference publications from 2015 to 2020.

Prof. Wang's primary research interests are data visualization and visual analytics, specifically on the topics of time-varying multivariate data visualization, flow visualization, graph visualization, information-theoretic algorithms, graph-based techniques, and deep learning solutions for big data analytics. He has published more than 90 peer-reviewed journal and conference papers, including more than 20 IEEE Transactions on Visualization and Computer Graphics (TVCG) journal and IEEE VIS conference papers. His research has been mainly supported by the U.S. National Science Foundation (NSF). Since 2009, he has served as the principal investigator (PI) or a co-PI of ten NSF grants.

Prof. Wang has graduated six Ph.D. and two M.S. students. His students have won four Best Paper and Honorable Mention Awards, three University Finishing Fellowships, one Dean's Award for Outstanding Scholarship, three Department Outstanding Research and Teaching Assistant Awards, and one Honorable Mention for the CRA Outstanding Undergraduate Researcher Award. Currently, the VisLab has five Ph.D. students (including three co-advised Ph.D. students), one M.S. student, and five undergraduate students.

2. Current research directions

The VisLab's current research directions include machine learning for visualization, flow visualization, time-varying multivariate data visualization, visual analytics, and visualization in education.

2.1. Machine learning for visualization

With the advent of deep learning, the renaissance of artificial intelligence as a viable solution for solving challenging computer vision and natural language processing problems has quickly swept across a wide variety of science and engineering fields. Many problems in scientific data analysis and visualization share inherent similarities with image or video processing, making deep neural networks a promising candidate for effectively solving scientific visualization problems.

Among the pioneers studying this research, members of the VisLab target 3D scalar and vector data that are most commonly produced from scientific simulations. In these scenarios, scientists often can only store a small fraction of simulation data output in the reduced form due to the stringent constraints on data storage and movement. Our goal is to augment these reduced simulation data using a deep learning approach. Image data augmentation refers to a technique that artificially creates new training data from existing training data via cropping, flipping, and warping, etc. Instead, we define *data augmentation* in our context as the addition of spatial, temporal, and variable details to reduced data by incorporating information derived from internal and external sources.

Working with the existing scientific workflow, we aim to provide an alternative to augment domain scientists' ability to tackle the big data problem. We output reduced simulation data in situ, perform offline network training, and enable online or offline super-resolution generation or data reconstruction. As shown in Fig. 1, our current research along this direction includes spatial and temporal super-resolution for time-varying data (Han and

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https://doi.org/10.1016/j.visinf.2020.09.001

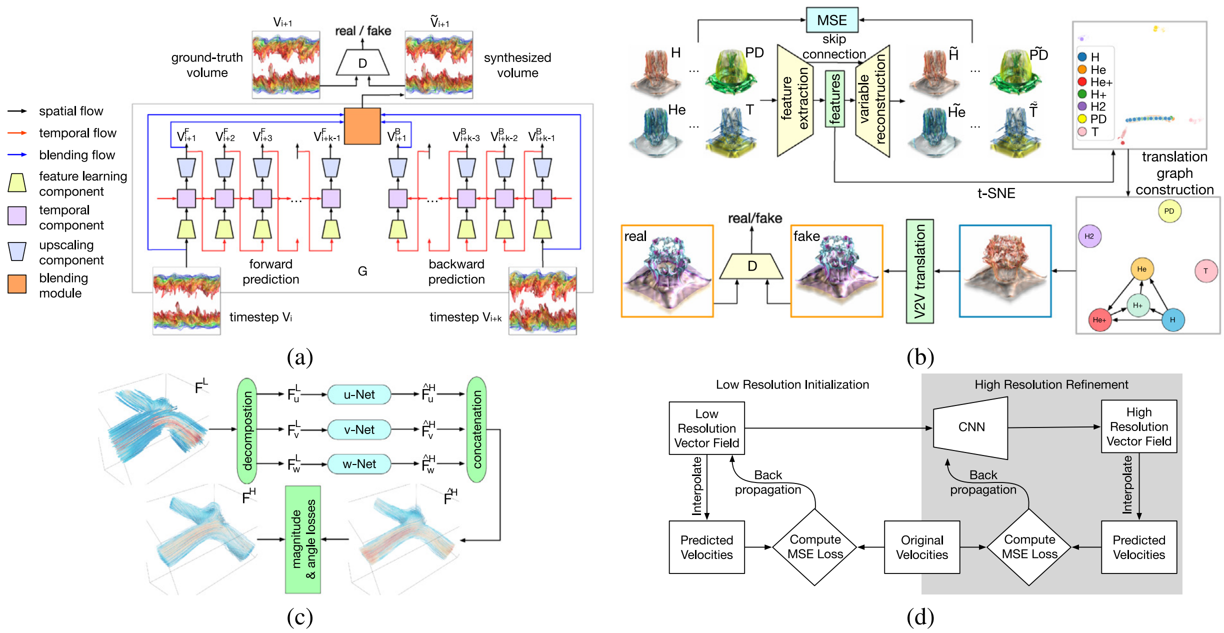


Fig. 1. Overview of the deep learning solutions for (a) temporal super-resolution for time-varying data (Han and Wang, 2020a), (b) variable selection and translation for multivariate time-varying data (Han et al., 2021), (c) spatial super-resolution for vector field data (Guo et al., 2020), and (d) vector field reconstruction using streamlines (Han et al., 2019).

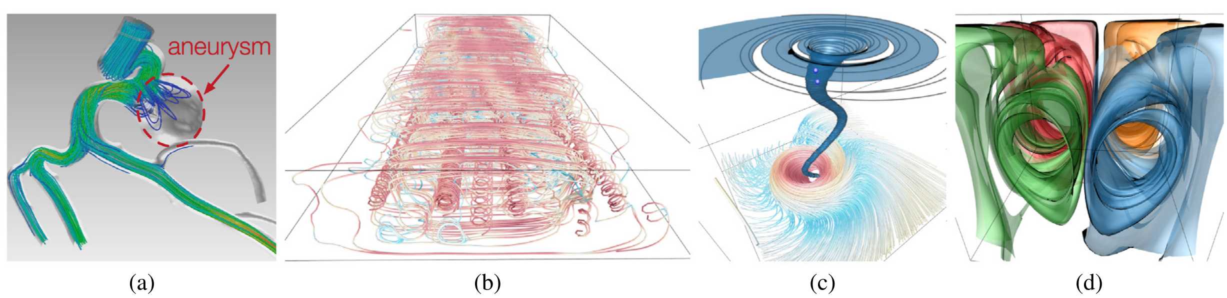


Fig. 2. (a) The blood flow nearby one terminal aneurysm at the middle cerebral artery (Tao et al., 2016a). (b) As the reduced data representation, flow lines are used to analyze rapidly-changing electromagnetic properties of superconductivity through vector data reconstruction (Han et al., 2019). (c) Flow lines and surface depict the swirling and twisting patterns of a procedurally-generated tornado (Tao and Wang, 2016). (d) The two swirls at the wingtips of an aircraft, tracing the wake vortices (Han et al., 2020).

Wang, 2020b,a), variable selection and translation for multivariate time-varying data (Han et al., 2021), super-resolution for vector field data (Guo et al., 2020), and vector field reconstruction using flow lines (Han et al., 2019).

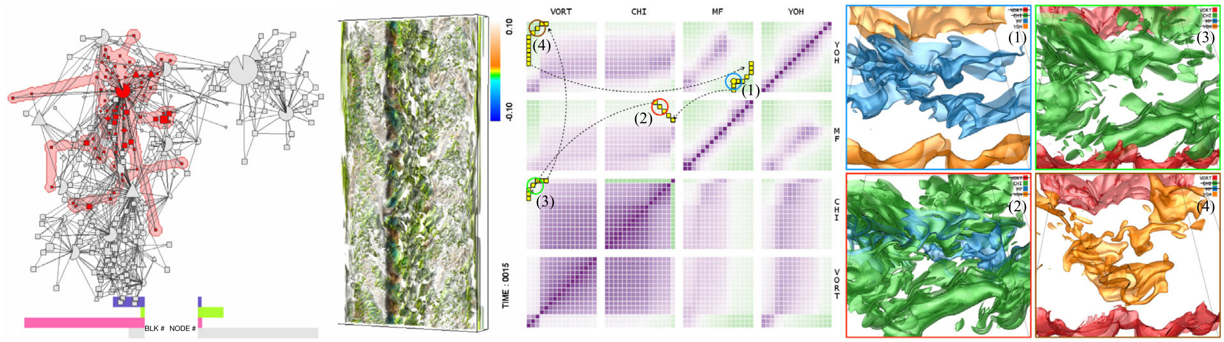
Besides data augmentation, we are also interested in *representation learning* from scientific data leveraging convolutional neural networks (CNNs) and graph neural networks (GNNs). These frameworks are general and robust, capable of learning latent feature descriptors implicitly from volumetric and surface data, eliminating the need for explicit feature engineering. The learned data and feature representations can be used for subsequent tasks such as dimensionality reduction, interactive clustering, and representative selection (Han et al., 2020; Porter et al., 2019).

2.2. Flow visualization

Understanding large and complex 3D flow fields is vitally important in many aero- and hydro-dynamical systems that dominate various physical and natural phenomena. Applications that study these systems, such as computational fluid dynamics (CFD), automotive and aircraft design, modeling of natural disasters (e.g., earthquakes, hurricanes, tornados), generate large amounts of vector field data that need to be analyzed and visualized. Most fluids (air, water, etc.) are transparent, and thus their flow patterns are invisible to us. Flow visualization makes the flow patterns visible so that we can visually acquire qualitative and quantitative flow information. Fig. 2 shows examples of flow visualization generated from our research.

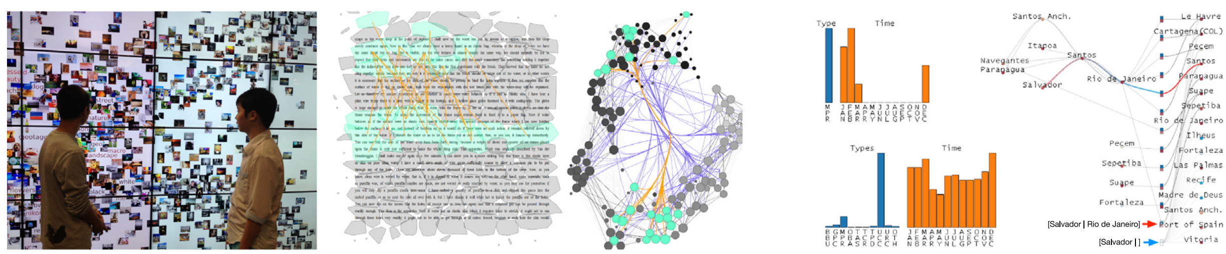
Supported by an NSF CAREER grant, the VisLab has conducted a series of research works to address critical challenges in integration-based flow visualization by presenting new solutions for analyzing and exploring flow lines (e.g., streamlines, pathlines). These works include (1) selecting representative flow lines based on information theory (Ma et al., 2013a; Tao et al., 2013), (2) extracting features from flow lines for segmentation and similarity analysis (Li et al., 2014, 2015), (3) creating robust visual characters and words from flow lines for shape analysis and organization (Tao et al., 2014, 2016b), (4) introducing interfaces and interactions for intuitive retrieval of partial flow lines (Tao et al., 2014, 2016b) and examination of hierarchical flow lines and their spatiotemporal relationships (Ma et al., 2013b, 2014a; Tao et al., 2018), and (5) devising streamline repositioning for focus+context viewing (Tao et al., 2014b) and automatic tour for examining hidden or occluded flow features (Ma et al., 2014b, 2019).

For the popular integration-based techniques for flow visualization, *line-based* techniques have made significant advances



(a) (b)

Fig. 3. (a) A mining approach that automatically extracts meaningful features from a graph-based representation for exploring time-varying volumetric data (Gu et al., 2016). (b) A variable traversal path using the matrix of isosurface similarity maps along with four animation frames corresponding to the path (Tao et al., 2019).



(a) (b) (c)

Fig. 4. (a) iGraph for exploring the MIR Flickr data set running on the 24-tile display wall (Gu et al., 2015, 2017a). (b) ETGraph for organizing the eye-tracking data to illustrate the reading patterns (Gu et al., 2017b). (c) HoNVis for investigating higher-order dependencies of the global ocean shipping network (Tao et al., 2017).

over the years, providing a sharp contrast to *surface-based* techniques. Flow surfaces can provide better illustrative capabilities and much-improved visualization than flow lines. However, existing methods for surface-based flow visualization still face substantial challenges of surface selection, visualization, and analytics, calling for creative ideas and novel solutions. Recently, we presented a sketch-based interface for semi-automatic stream surface generation (Tao and Wang, 2016, 2018). The VisLab is developing a machine learning assisted visual analytics approach for understanding 3D complex flow surfaces. Leveraging techniques from deep learning, shape analysis, and visual analytics, we aim to develop a new framework that supports (1) selection of representative surfaces through feature learning, projection, and clustering powered by GNNs, (2) exploration of surface patterns via a principled vocabulary-based method for shape-invariant partial flow surface querying and matching, and (3) comparative analytics of flow surfaces for studying seeding sensitivity via a river-like visual metaphor.

2.3. Time-varying multivariate data visualization

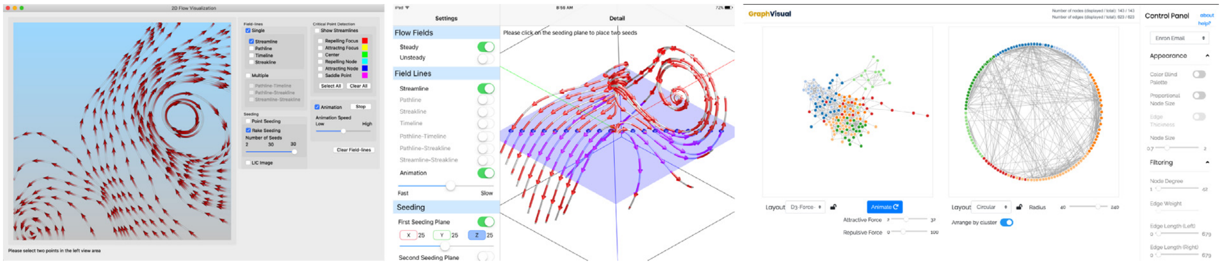
Many scientific simulations produce time-varying multivariate volume data that can span hundreds or thousands of time steps and consist of tens of variables. Additionally, ensemble data sets are common nowadays, where a simulation is conducted in multiple runs with different configurations. This leads to the multiplied amount of data to be studied. Understanding the underlying physical phenomena in this kind of data often requires key insights to be discovered through observations. This need places analysis and visualization of time-varying multivariate data at the heart of scientific visualization. Fig. 3 shows examples of time-varying multivariate data visualization generated from our research.

Time-varying multivariate data visualization has been a research focus of Prof. Wang dated back to his Ph.D. research. At that time, the study focused on organizing the data in a multiresolutional manner to support efficient and effective retrieval and rendering (Wang and Shen, 2004; Wang et al., 2005; Wang and Shen, 2005, 2006; Wang et al., 2007). The focus later shifted to statistical, correlation, importance, and influence analysis and visualization (Wang and Ma, 2008; Wang et al., 2008; Sukharev et al., 2009; Gu and Wang, 2010; Chen et al., 2011; Wang et al., 2011) as well as transforming the high-dimensional spatiotemporal data into abstract views for visual reasoning, mining, and analytics (Gu and Wang, 2011, 2013; Gu et al., 2016; Tao et al., 2016a). The VisLab is investigating *representative selection* for summarizing isosurfaces, time steps, and variables to support effective visual exploration and understanding of large-scale time-varying multivariate data sets (Imre et al., 2017, 2018; Tao et al., 2019; Porter et al., 2019). Deep learning techniques for representation learning will be employed in this study.

2.4. Visual analytics

Visual analytics enables analytical reasoning facilitated by interactive visual interfaces and gains popularity as the fastest-growing branch of visualization research because it applies to a wide variety of domains and applications. Since 2015, the VisLab has applied visual analytics techniques to explore large image and text collections (Gu et al., 2015, 2017a), eye-tracking data (Gu et al., 2017b), global ocean shipping networks (Tao et al., 2017), conference navigator data (Bailey et al., 2018), course clickstream and student performance data (Goulden et al., 2019; Deng et al., 2019), and ant movement data (Hu et al., 2020). Fig. 4 shows examples of our visual analytics research works.

Teaming up with scientists, designers, and engineers from Notre Dame Learning, members of the VisLab are focusing on



(a) (b) (c)

Fig. 5. The user interfaces of (a) FlowVisual desktop and (b) FlowVisual app show rake seeding for streamline tracing and animated streamline visualization in 2D and 3D, respectively. (c) The web interface of GraphVisual shows the same graph data set in two different layouts.

learning analytics research. Our goal is twofold. First, we aim to identify and help to close the academic performance gaps resulting from disparities in student backgrounds and preparations in college-level science, technology, engineering, and mathematics (STEM) gateway courses. Second, we aim to analyze the impact of STEM gateway course performance on downstream required courses and identify common pathways to academic success. The research outcome is expected to benefit major stakeholders, including students, instructors, advisors, and administrators.

2.5. Visualization in education

Visualization has become an indispensable means for analyzing data generated from a wide variety of applications that span many STEM fields. As more and more colleges and universities pay attention to research and education in data science and human-centered computing, adding a new course of Data Visualization into the curricula becomes a growing trend. Following this trend is a significant need for high-quality curriculum materials that can assist in teaching visualization knowledge and training the STEM workforce for tomorrow. Although visualization research has advanced for 30 years, visualization education has lagged: visualization textbooks only started to emerge in the past decade, and pedagogical software tools that assist the teaching and learning of data visualization are scarce.

Along the direction of visualization in education, the VisLab's research is to develop the VisVisual software toolkit (Anon, 2020b) for teaching and learning important yet challenging visualization concepts and algorithms. The proposed toolkit consists of four tools: VolumeVisual, FlowVisual, GraphVisual, and TreeVisual. Together they cover scalar and vector field visualization in scientific visualization and graph and tree drawing in information visualization. The pilot FlowVisual tool (Wang et al., 2013, 2016) has proven successful: since 2013, the website has been visited 22,000+ times, and the tool has been downloaded 1700+ times. Fig. 5(a) and (b) show the interfaces of FlowVisual desktop and app versions. GraphVisual (Imre et al., 2020) has recently completed its development and deployment. Fig. 5(c) shows the web interface of GraphVisual. The VisLab is developing VolumeVisual and TreeVisual.

3. Facilities

Members of the VisLab have access to Notre Dame's Center for Research Computing (CRC). The CRC is a member of the Open Science Grid and is home to the Northwest Indiana Computational Grid—a consortium of research institutions including Argonne National Laboratory, Purdue University, and the University of Notre Dame. The CRC provides the following services and resources in support of research and education within Notre Dame and the local community:

- computational resources: over 25,000 CPU cores in systems of various architectures and interconnects with associated disk systems for short-term storage;
- storage resources: approximately 3 PB of data storage including disk-based systems for high-performance and user-space storage of data and tape-based systems for long-term storage;
- specialized resources: visualization systems, systems for virtual hosting, prototype architectures, and infrastructure for high-throughput computing; and
- access and interface to the TeraGrid and Open Science Grid.

Prof. Wang is a co-PI of an NSF CRI grant in which we requested a GPU cluster for computer science research. The first version of the cluster has been up and running since October 2016, which includes

- eight Quantum TXR231-1000R servers with dual Intel Xeon 12-core CPU E5-2650 v4 @ 2.20 GHz, 128 GB RAM, and four NVIDIA Titan Xp GPU accelerators;
- eight Quantum TXR231-1000R servers with dual Intel Xeon 12-core CPU E5-2650 v4 @ 2.20 GHz, 128 GB RAM, and four NVIDIA Tesla P100 GPU accelerators.

The Fall 2018 upgrade includes three NVIDIA Titan Xp and two NVIDIA Tesla V100 GPU accelerators, further boosting the performance of deep learning algorithms. The GPU cluster has led to transformative research in computer science by enabling the discovery of novel algorithms and methods previously inaccessible, incubating new research projects, and enhancing multidisciplinary collaboration between computer scientists and their peers in other disciplines. Members of the VisLab are active users of this GPU cluster.

4. International collaborations

The VisLab has received support from Notre Dame's Luksic Family Collaboration Grant Program, Global Collaboration Initiative Program, and Asia Research Collaboration Grant Program. Members of the VisLab have collaborated with oversea institutions, including the Pontifical Catholic University of Chile, the Chinese Academy of Sciences, Zhejiang University, Shandong University, Sun Yat-sen University, and Technical University of Munich. These collaborative efforts have led to 13 papers (11 published, two under review). Since 2016, the VisLab has hosted 20 undergraduate students from leading universities in China and Ireland for various summer research projects through Notre Dame's International Summer Undergraduate Research Experience (iSURE) Program and Naughton Fellowships Program. These joint efforts have led to ten papers (eight published including one award-winning paper, two under review). Many of these undergraduate students later pursued their graduate study and research at prestigious universities such as Carnegie Mellon University, Columbia

University, University of California, Berkeley, University of Cambridge, University of Illinois at Urbana–Champaign, University of Southern California, and University of Wisconsin–Madison.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The research works described in this article have been supported by the U.S. National Science Foundation through grants IIS-1017935, CNS-1229297, IIS-1456763, IIS-1455886, CNS-1629914, DUE-1833129, and IIS-1955395.

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