the video novice to convey the message effectively, making good use of annotation and motion. For greatest effectiveness, scientists really need to incorporate the type of design expertise found in film and television studios. They also need better tools to control such technological aspects as aliasing, temporal filtering, and color gamut mapping.

Strategies

How do we ensure that research on developing visualization models is undertaken with the imperative we feel is required? For example, several previous visualization workshops have highlighted the need for reference models, but the models themselves are few. And we have not seen a comparison of visualization reference models with existing graphics reference models, apart from some early pipeline-oriented discussions.

Perhaps the most effective way of overcoming the reluctance to formalize models in an evolving field is to establish special sessions at a visualization conference, for example, at the IEEE Visualization conference. Such a session could propose initial models from which progress could emerge in a one- to two-year time frame. We might expect standardization on a reference model and the components of such a model, including data, user, time, and device models, in around five years.

Validation requires enough attention to ensure that, as computational platforms offer the performance needed for visualization, we can have confidence in the validity and effectiveness of the tools we develop and use. Clearly, a disciplined effort is needed to establish test data sets and results and to benchmark commercial software. The supercomputing community found this necessary to maintain research and commercial credibility, and there is every reason to suggest that the visualization community will have to do the same. Industry and research consortia, perhaps through a dedicated workshop or through a major society such as ACM or IEEE, are best placed to undertake reproducibility test design.

Research groups will need to determine how to test the effectiveness of visualizations by establishing a major focus in this area, drawing from expertise in psychology and cognitive science. While there is some effort in this area, substantially more is required to give us real faith in the visualizations we produce.

We believe that computer scientists can help improve the integration of tools and techniques within visualization environments by applying modern software engineering approaches to many of the problems. We need research into the design of systems that are sufficiently flexible to allow for minimal latency of interaction, for example, over a distributed computing environment. Achieving interoperability, effective distributed systems, and progressively more automated generation of visualizations are significant research problems that will take some years to result in commercially available systems.

However, consortia of research and industry group could address some aspects of system limitations, for example, establishing default parameters, making database interfaces available, standardizing on multimodal device interfaces, and standardizing on device-independent color coordinate systems. Successful efforts in these areas could make current systems more usable within a one- to three-year time frame. ❑

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References

1. R.B. Haber and D. McNabb, "Visualization Idioms: A Conceptual Model for Scientific Visualization Systems," in *Visualization in Scientific Computing*, G. Nielson and B. Shriver, eds., IEEE Computer Society Press, Los Alamitos, Calif., 1990.
2. D.M. Butler et al., "Visualization Reference Models—Panel Summary," *Proc. IEEE Visualization 93*, IEEE CS Press, Los Alamitos, Calif., 1993, pp. 337-342.
3. L.A. Treinish et al., "Data Models, Structures, and Access Software for Scientific Visualization—Panel Summary," *Proc. IEEE Visualization 93*, IEEE CS Press, Los Alamitos, Calif., pp. 355-361.
4. K.W. Brodlie et al., *Scientific Visualization: Techniques and Application*, Springer-Verlag, New York, 1992.
5. R.B. Haber, B. Lucas, and N. Collins, "A Data Model for Scientific Visualization with Provisions for Regular and Irregular Grids," *Proc. Visualization 91*, IEEE Computer Society Press, Los Alamitos, Calif., 1991, pp. 298-305.
6. W. Ribarsky et al., "Object-Oriented, Dataflow Visualization Systems—A Paradigm Shift?" *Proc. IEEE Visualization 92*, IEEE CS Press, Los Alamitos, Calif., 1992, pp. 384-388.
7. M.M. Thalmann and D. Thalmann, *Computer Animation: Theory and Practice*, 2nd ed., Springer-Verlag, Tokyo, 1990.
8. M.M. Thalmann and D. Thalmann, ed., *Virtual Worlds and Multimedia*, John Wiley and Sons, New York, 1993.
9. W. Hibbard, C. Dyer, and B. Paul, "Display of Scientific Data Structures for Algorithm Visualization," *Proc. Visualization 92*, IEEE CS Press, Los Alamitos, Calif., 1992, pp. 139-146.
10. R.A. Earnshaw, M.A. Gigante, and H. Jones, eds., *Virtual Reality Systems*, Academic Press, New York, 1993.

Research Issues in Vector and Tensor Field Visualization

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Flow visualization has long been a part of fluid dynamics research. We have photographs from the 19th century that show the patterns resulting from the insertion of ink, smoke, or particles in a fluid. This strong relation has become even stronger in the era of computer data generation and analysis. Today, computational fluid dynamics (CFD) research is almost impossible without computer-generated visualizations of the very large amounts of data resulting from numerical simulations.

Although good techniques now exist for analysis of scalar data, most existing techniques for the visualization of vector

Table 1. Classification of some existing visualization techniques.			
Technique	**Order of Data**	**Domain**	**Level**
Volume ray casting	Scalar	Volume	Elementary
Isosurface	Scalar	Surface	Elementary
Arrow plot	Vector	Point	Elementary
Stream surface	Vector	Surface	Elementary
Particle animation	Vector	Point	Elementary
Tensor probe[9]	Vector	Point	Local
Vector field topology[6]	Vector	Volume	Global
Hyperstreamlines[1,3]	Tensor	Line	Elementary

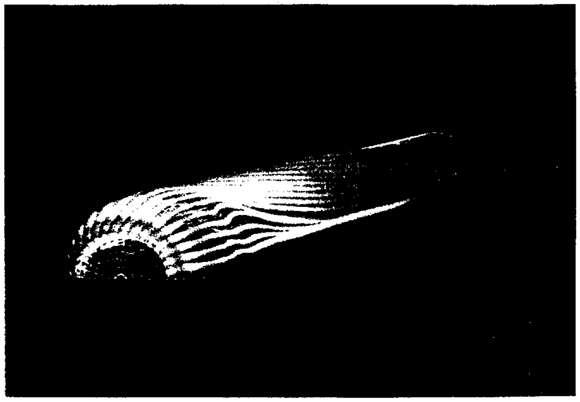

Figure 1. Hyperstreamlines completely encode tensor data along continuous trajectories.[3] They are surfaces built around curves tangent to one of the eigenvectors of the tensor field. The cross section encodes locally the two eigenvectors orthogonal to the trajectory. In the figure, the trajectory, cross-section diameter, and color of the hyperstreamlines encode the velocity direction, pressure, and kinetic energy density, respectively.

fields—the predominant data type in CFD—meet only part of what is required. Common techniques such as arrow plots, streamlines, and particles work well for 2D applications, but for 3D data sets they often lead to cluttered displays. The main reason for this difficulty is a fundamental one: There is no intuitive and psychologically meaningful method to visualize 3D flows. We can represent a single vector by an arrow, but no such physical metaphor exists for a field of vectors. For tensors, which are much more complex and abstract entities, the problem is even more severe.

This situation presents an interesting challenge to the visualization community. There is a real need for visualization, but there are no simple solutions. In the past five years many researchers have recognized this challenge and developed new techniques. We have given overviews elsewhere,[1-3] so we restrict ourselves here to open research issues.

We proceed in three ways. First, we propose a classification of existing vector and tensor field visualization techniques based on work by Delmarcelle and Hesselink[1,3] and point out research gaps in this classification scheme. Second, we discuss feature-based visualization, which shows higher level descriptions derived from elementary data. Third, we consider the role of visualization in the research process, again revealing gaps in our current know-how concerning visualization of vector and tensor fields.

Classification and research issues

We can classify vector and tensor field visualization techniques in different ways. The simplest distinction is by the order of the data we wish to visualize: scalar, vector, and tensor data. Next, we can distinguish by the spatial domain dimensionality of the visualization objects: points, lines or curves, surfaces, and volumes. The next distinction is more subtle: the information level. The information shown at a certain point can refer to only the elementary data at that single point, or it can indicate gradient values in a region of space, and it can extend this region into larger areas—up to the full domain of data support. The corresponding three information levels are elementary, local, and global.

Table 1 classifies some existing visualization techniques according to order, domain, and information level.

Table 2. Possible new vector field visualization techniques.			
Technique	**Order of Data**	**Domain**	**Level**
Extensions of volume rendering	Vector	Volume	Elementary
Stream surfaces with gradient cues	Vector	Surface	Local
Area glyphs	Vector	Point	Global

The complete 3D classification has 36 cells, many of which are still (almost) empty. Not all cells are equally meaningful, but we need new techniques for many of them. This need is particularly pressing for local and global visualization of tensor fields, for which only a few techniques are available (see Figure 1).

But even for vector fields we need new techniques. Table 2 presents three examples: extension of direct volume rendering for vector fields, stream surfaces with additional cues on the gradients perpendicular to the surface, and glyphs that summarize the characteristics over an area of a vector field. The table classifies these combinations in the same way Table 1 classifies existing techniques, thereby filling in some of the empty spaces in the original classification.

The development of these techniques is based on an underlying philosophy: On the one hand, we need techniques that show all data at an elementary level for the whole domain, and on the other hand we need techniques to summarize data over a larger area at a single point. Feature visualization offers new possibilities for this.

Feature visualization

We define a feature as anything contained in a data set that might be of interest for interpretation. The vagueness of the def-

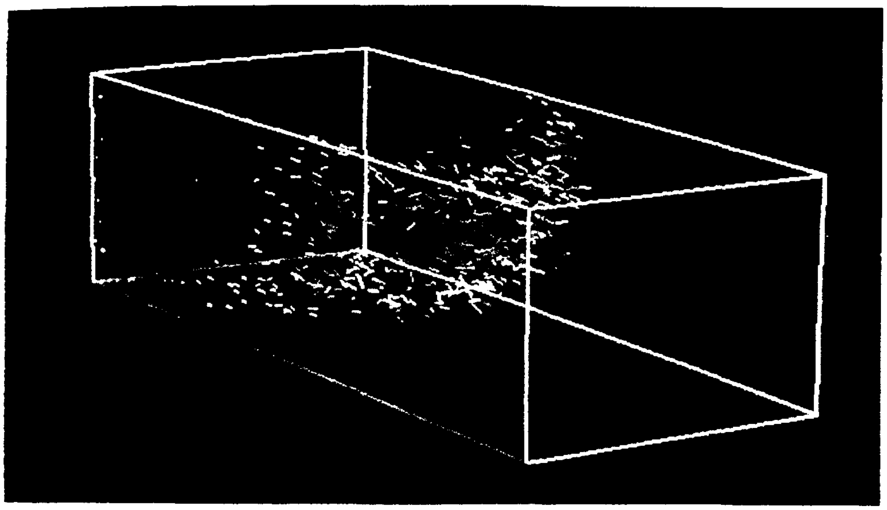

Figure 2. Explicit feature visualization: a turbulent channel flow.[4] In the flow simulation, two separate data fields were computed: a mean velocity field and a turbulence intensity field. For visualization, particle motion is used to reconstruct the turbulent fluid motions. At each step of the particle path, a stochastic perturbation is determined from local turbulence intensity and added to local velocity. This results in erratic particle motions, reflecting turbulent dynamics.

inition is deliberate, as the nature and type of features vary strongly with the application area, the measurement or simulation methods, the phenomena studied, and the aim of the research. A feature-based data representation is a high-level data description that can replace the original representation in a more compact, clear, and meaningful manner. Important characteristics are extracted for further analysis and for emphasis in visualization. The goals are to reduce complexity, to increase information content, and to match the concepts of the application area.

In medical imaging, much work has been done on feature extraction from scalar fields. Segmentation techniques are used to classify tissue types and extract the features of human anatomy from computed tomography (CT) or nuclear magnetic resonance (NMR) scan data.

Several researchers have also worked on feature-based visualization of vector and tensor data (for a brief survey, see Post and Van Wijk[2]). We can distinguish several types of features. First, a feature can be a part of the data that satisfies some user-specified criterion of interest. This criterion is used to filter the data and extract the items of interest. A second type of feature is a region of interest, found as a result of a decomposition of the study domain (spatial or temporal). A third class consists of characteristic patterns, such as critical points and their local configurations, or meaningful physical "objects" such as vortices or shock waves.

There are several ways to visualize features. When a numerical simulation generates separate feature data, the features are already explicit in the raw data for visualization. An example is a simulation of turbulent flow,[4] which generates a mean velocity field and an extra turbulence intensity field. Visualization involves a reconstruction of the features (in this case turbulent motions) in the mean flow (see Figure 2).

The opposite approach is to visualize the data containing the features directly and to select a visualization mapping in such a way that features emerge from the displayed images. The viewer detects such implicit features through eye-brain processing. An example from CFD research is the visualization of hairpin vortices in turbulent flows, using isosurfaces of low-pressure or high-vorticity magnitude.[5]

Finally, we can extract features from the data for further analysis and interpretation. The extraction can occur separately from the data-generation phase of the visualization process by applying feature-extraction algorithms during the data-enhancement phase. Examples are the vector field topology techniques of Helman and Hesselink,[6] and other techniques from image processing and mathematical morphology.[7,8]

A general scheme for feature extraction and visualization consists of a sequence of steps. First, the user must specify the characteristics of the features of interest. Such a specification might merely define a combination of attributes, such as local extrema or global threshold data values. But the specified feature might also be a physical phenomenon or a persistent pattern that behaves like an object. It is the task of the feature extractor to derive from this specification an appropriate general extraction technique. In the latter case, the feature definition is likely to be more application dependent. To derive an extraction technique, a visualization system might contain domain-specific knowledge or intelligence that allows high-level interactive feature specification.

Next, algorithms must extract these features from the data and store them in a high-level form. To visualize these features, the system maps them to icons that are finally displayed on the screen. Representation by icons is very important for feature visualization. In this context, an icon is any geometric object that represents data by geometric attributes, such as size and shape, or other visible attributes, such as color or opacity. Icons range from simple objects (curves and surfaces) to abstract symbolic objects (glyphs).

Hesselink and Delmarcelle[1,3] have discussed vector and tensor data visualization techniques in terms of iconic representations. Most existing icons represent the data on a low level of abstraction. Feature-based visualization requires the development of new icon types to encode high-level concepts. This icon type has been used for representing critical points and their classification.[6] Another example is the icon used for visualizing local velocity and velocity gradients.[9] This icon was designed as a probing device for interactive data exploration (see Figure 3). The design of multivariable icons is a separate area of study, as is the identification of "natural" mappings of data quantities to such icon attributes as shape and color.

By definition, feature visualization concerns the meaning of data, thus the techniques are always liable to be application-

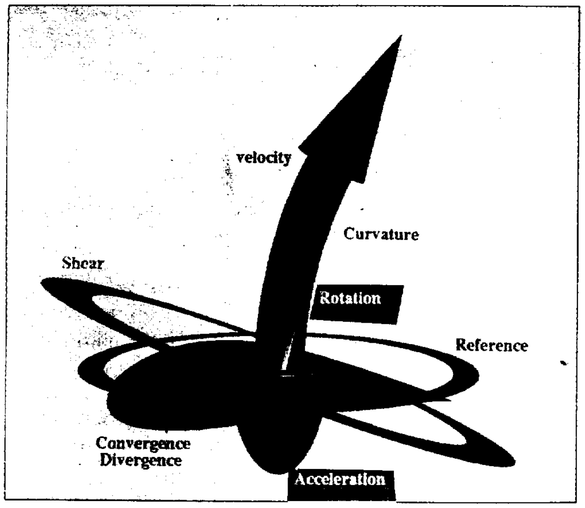

Figure 3. A probe for the local inspection of flow fields.[9] This is a typical example of a technique that shows data for a point at a local level. Not only the velocity vector but also the local variation of the velocity are visualized in a glyph. The tensor that describes this variation is decomposed into five components (curvature, acceleration, shear, convergence, and twist), which are mapped onto geometric primitives.

specific. In visualization research we must develop generic techniques and allow users to specify their features or selection criteria according to the application area and the purpose of analysis. It is too early to determine to what extent this is possible, but a wider application of analysis techniques from image processing and mathematical morphology, and of techniques and concepts from the mathematics of vector and tensor fields, may be very fruitful.

In our view, the main thrust of vector and tensor field visualization research should be in this area. We base this view on the observation that currently known techniques show highly promising results.

Visualization and research practice

Visualization is embedded in the scientific and engineering research process. This process uses both experimental and mathematical modeling and simulation methods, often in combination. In this section, we consider problems that arise from the use of visualization as part of the research process and suggest some research topics to improve its effectiveness. Most of these remarks apply to scientific visualization in general, rather than specifically to vector and tensor fields.

An important but little-investigated problem is the comparison of multivariate data sets from different sources. An obvious need is the validation of numerical simulation models by comparison with numerically generated and measured data. This type of comparison is becoming feasible through experimental techniques that produce data sets with the same information content as numerical simulations (for example, particle image velocimetry in fluid dynamics). In the simplest form, we can compare images by looking at them side by side or superimposed on each other. More advanced approaches require the development of common high-level representations (such as feature-based representations), metrics, and special visualization tools for comparing data. Initial results from these developments are urgently needed and should become available in the next three to five years.

A related issue is the development of indicators of accuracy and reliability in visualization. In most experimental sciences, documenting errors is standard practice, but it is not yet so for computer-generated visualizations. Possibly these indicators should be an integrated part of the whole visualization process, from measurement or numerical simulation to the visualization itself. As a minimum, we should provide visual clues to promote error awareness.

Related to these issues, the visualization techniques themselves must be validated and evaluated. Important aspects are correctness (error measure) and usefulness and effectiveness (psychological meaningfulness) in generating insight and knowledge. These all depend on the human capacity to perceive and understand not only structural relations (shape, spatial ordering, patterns) but also quantitative relations in the spatial and temporal domain (relative and absolute values, and rates of change). Only field testing or laboratory research with human subjects can support this type of evaluation. It should be an ongoing activity in the visualization research community, producing results in the next five years.

A final remark

Extensive efforts by a large number of researchers have resulted in many colorful, and sometimes even beautiful visualizations. In spite of this, we have seen that many problems in vector and tensor field visualization still await solutions. The reason, we suggest, is intrinsic: Vector and especially tensor fields are complex data describing complex physical phenomena, which are themselves often poorly understood. Visualization of these data is an interesting and challenging research area. □

References

1. L. Hesselink and T. Delmarcelle, "Visualization of Vector and Tensor Data Sets," to be published in *Frontiers in Scientific Visualization*, L. Rosenblum et al., eds., Academic Press, New York, 1994.
2. F.H. Post and J.J. van Wijk, "Visual Representation of Vector Fields," to be published in *Frontiers in Scientific Visualization*, L. Rosenblum et al., eds., Academic Press, New York, 1994.
3. T. Delmarcelle and L. Hesselink, "A Unified Framework for Flow Visualization," to be published in *Engineering Visualization*, R. Gallagher, ed., CRC Press, Boca Raton, Fla., 1994.
4. A.J.S. Hin and F.H. Post, "Visualization of Turbulent Flow with Particles," *Proc. Visualization 93*, IEEE Computer Society Press, Los Alamitos, Calif., 1993, pp. 46-52.
5. P. Comte, "Visualization of Turbulent Coherent Structures in Numerical Wind Tunnels," Course Notes, summer course on Principles of Visualization in Fluid Mechanics, J.M. Burgers Centre for Fluid Mechanics, Delft, Netherlands, Aug. 24-28, 1992.
6. J. Helman and L. Hesselink, "Visualizing Vector Field Topology in Fluid Flows," *IEEE CG&A*, Vol. 11, No. 3, May 1991, pp. 36-46.
7. D. Silver and N.J. Zabusky, "Quantifying Visualizations for Reduced Modeling in Nonlinear Science: Extracting Structures from Data Sets," *J. Visual Communication and Image Representation*, Vol. 4, No. 1, Mar. 1993, pp. 46-61.
8. J. Villasenor and A. Vincent, "An Algorithm for Space Recognition and Time Tracking of Vorticity Tubes in Turbulence," *CVGIP: Image Understanding*, Vol. 55, No. 1, Jan. 1992, pp. 27-35.
9. W.C. de Leeuw and J.J. van Wijk, "A Probe for Local Flow Field Visualization," *Proc. Visualization 93*, IEEE Computer Science Press, Los Alamitos, Calif., 1993 pp. 39-45.