

Streamline Selection and Viewpoint Selection via Information Channel

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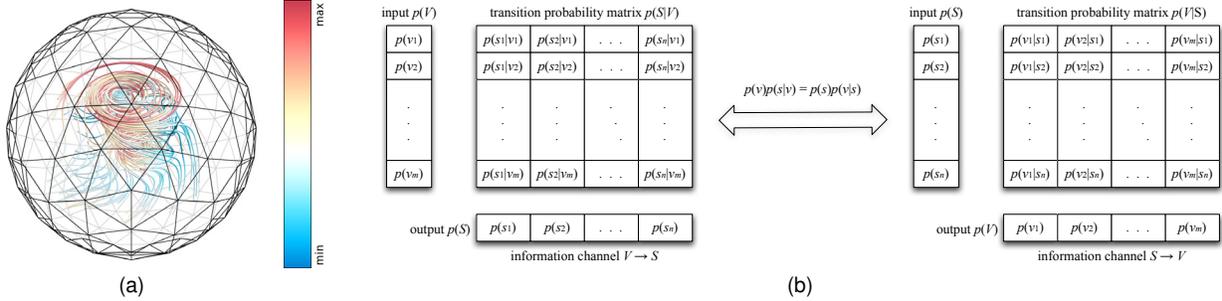


Figure 1: (a) Sample viewpoints are constructed along a sphere from the recursive discretization of an icosahedron. Velocity magnitudes are mapped to streamline colors. (b) The information channel $V \rightarrow S$ and the inverted channel $S \rightarrow V$ are connected via the Bayes theorem.

ABSTRACT

We propose to solve streamline selection and viewpoint selection automatically in a unified and rigorous information-theoretic framework. This is achieved by building two interrelated information channels between a pool of candidate streamlines and a set of sample viewpoints. We define streamline information to select best streamlines and in a similar manner, define viewpoint information to select best viewpoints. We demonstrate the effectiveness of our approach by showing experimental results with several 3D flow data sets of different sizes and characteristics.

1 MOTIVATION

Effective streamline visualization can be formulated as the problem of *seed placement* or *streamline selection*. Seed placement aims at carefully placing seeds in the domain to generate streamlines that capture flow features. Streamline selection aims at carefully selecting streamlines from a large streamline pool for effective display. Streamline seeding for 2D and 3D vector fields has been well studied and continues to receive much attention. Compared to selecting seeds, selecting streamlines is directly related to the final visualization results. With the rapid advances of general-purpose computing on GPUs, it is quite affordable nowadays to generate a large pool of streamlines. As such, streamline selection has become a promising alternative to seed placement and has received increasing attention [3, 2]. Besides streamline selection, selecting good viewpoints is also critical for understanding large and complex 3D flow fields. This is because automatically guiding the viewers to good viewpoints improves both the speed and the efficiency of data understanding. While viewpoint selection for volume data has been extensively studied, the same issue for flow visualization remains to be thoroughly investigated.

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2 OUR APPROACH

We propose to model the problems of streamline selection and viewpoint selection in a single unified framework by considering a set of streamlines $S = \{s_1, s_2, \dots, s_n\}$ and a set of viewpoints $V = \{v_1, v_2, \dots, v_m\}$ as discrete random variables and building two interrelated *information channels* between them: $V \rightarrow S$ and $S \rightarrow V$. As shown in Figure 1, the main components in the channel $V \rightarrow S$ are the following: (1) the *transition probability matrix* $p(S|V)$ where $p(s|v)$ represents the probability of “seeing” streamline s from viewpoint v (i.e., the importance of s with respect to v); (2) the *input probability distribution* $p(V)$ where $p(v)$ represents the probability of selecting each viewpoint v ; and (3) the *output probability distribution* $p(S)$ where $p(s)$ represents the average probability that streamline s is “seen” from all viewpoints, i.e., $p(s) = \sum_{v \in V} p(v)p(s|v)$. Similarly, we can construct the inverted channel $S \rightarrow V$ with the new transition probability matrix $p(V|S)$, where $p(v|s)$ represents the probability of selecting viewpoint v given streamline s . These two channels are connected via the Bayes theorem, i.e., $p(v)p(s|v) = p(s)p(v|s)$, which provides us a means to compute $p(v|s)$ given $p(v)$, $p(s)$ and $p(s|v)$.

Previously, researchers have presented several algorithms on volumetric and polygonal data that were built upon similar information channels [1, 5]. Unlike voxels which are fine-grained elements and polygons which are fairly localized data items, a streamline could stretch across the entire field with a very complex shape. This unique challenge makes it difficult to analyze the conditional probability $p(s|v)$ for a streamline, which is the key for deriving the channel $V \rightarrow S$. To define $p(s|v)$, we consider two view-dependent factors: *mutual information* and *shape characteristics*. The mutual information $I(s; s_v)$ indicates how much information about streamline s is revealed in its 2D projection s_v under viewpoint v . To compute $I(s; s_v)$, we construct the 2D histograms by binning the direction and magnitude of vectors interpolated from the original flow field for all points along s and s_v , respectively. The shape characteristics $\alpha_{s,v}$ indicates how well (i.e., stereoscopic) the 3D shape of streamline s is reflected under viewpoint v . To compute $\alpha_{s,v}$, we consider the vector $\vec{p}_i \vec{p}_{i+1}$ formed by any two consecutive points along the streamline and calculate its angle θ with respect to the viewing vector \vec{v} . We map θ to $\alpha_{p_i, p_{i+1}; v}$ using a piecewise linear function where the maximum (minimum) is achieved when θ is 45° or 135° .

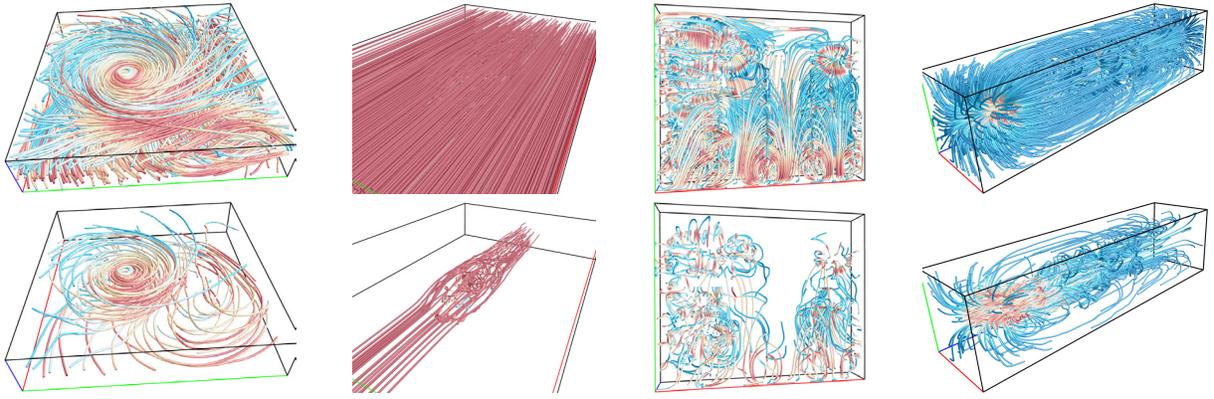


Figure 2: The initial pool of streamlines and the selection results. Left to right: hurricane (600 streamlines, 60 selected), car flow (600 streamlines, 40 selected), computer room (800 streamlines, 140 selected), and solar plume (600 streamlines, 100 selected).

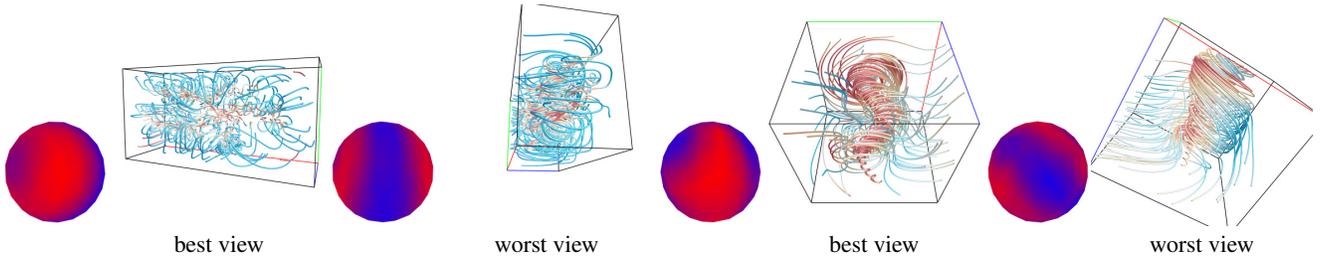


Figure 3: Viewpoint ranking. Left: the crayfish data set. Right: the tornado data set. In each of the view sphere images, red to blue is for the best viewpoint to the worst viewpoint. Streamline rendering from the best viewpoint and the worst viewpoint is also shown.

(0° , 90° , or 180°). $\alpha_{s,v}$ is computed as the average of all $\alpha_{p_i p_{i+1}, v}$, weighted by the length of their respective vector $\overrightarrow{p_i p_{i+1}}$. Finally, we define $p(s|v) = \alpha_{s,v} I(s; s_v) / \sum_{s \in S} \alpha_{s,v} I(s; s_v)$. With $p(s|v)$ defined, we define $p(v) = p(S|v) / p(S|V)$, where $p(S|v) = \sum_{s \in S} p(s|v)$ and $p(S|V) = \sum_{v \in V} p(S|v)$.

Leveraging these two symmetric information channels, we are able to perform streamline selection and viewpoint selection in a similar fashion. For streamline selection, we sort all the streamlines S into a priority queue. The sorting is based *streamline information* $I(s; V) = \sum_{v \in V} p(v|s) \log \frac{p(v|s)}{p(v)}$, which represents the degree of dependence between streamline s and the set of viewpoints V . We select the best streamlines according to the sorted order. To avoid selecting similar streamlines and reduce clutter, we check the pairwise distance between two streamlines using the mean of closest point distances, as suggested by Moberts et al. in DTI fiber clustering [4]. A streamline is not selected if its distance to any streamline previously selected is smaller than a given threshold. The selection process stops when a given number of streamlines is selected or all streamlines in the pool are considered. Viewpoint selection can be performed similarly by sorting all the viewpoints V based on *viewpoint information* $I(v; S) = \sum_{s \in S} p(s|v) \log \frac{p(s|v)}{p(s)}$. To avoid selecting similar viewpoints, we also check the pairwise distance between two viewpoints using the Euclidean distance between their corresponding vectors (i.e., $p(S|v) = \langle p(s_1|v), p(s_2|v), \dots, p(s_n|v) \rangle$).

We tried our approach with several flow data sets of different sizes and characteristics. Figure 2 shows the streamline selection results where the initial pool of streamlines was generated by dense placement of seeds randomly. Our streamline selection is able to reveal the features in the flow fields effectively. For example, for the car flow data set, our method is able to select important streamlines that are close to the car and discard the surrounding uninteresting streamlines that are nearly straight. In Figure 3, we show the ranking of viewpoints together with the corresponding best and

worst viewpoints. As expected, the view sphere images indicate that neighboring viewpoints have similar rankings and the viewpoint ranking varies gradually over the view sphere. For both data sets, the best viewpoint corresponds to a view where the flow detail is most clearly visible, and the worst viewpoint corresponds to a view where the flow features are most occluded.

3 FUTURE DIRECTIONS

We plan to compare our method against [3, 2] and conduct a user study to testify how well our streamline and viewpoint selection results comply with human perception, and if necessary, modify our solution accordingly by incorporating perceptual criteria such as saliency as an importance factor. Furthermore, our current framework only considers the full view of the flow field by placing the camera around a sphere enclosing the entire data set. We will also explore the case where the viewpoint is moved inside the flow field and the camera is placed around a local sphere for 360° viewing.

REFERENCES

- [1] M. Feixas, M. Sbert, and F. González. A unified information-theoretic framework for viewpoint selection and mesh saliency. *ACM Transactions on Applied Perception*, 6(1), 2009.
- [2] T.-Y. Lee, O. Mishchenko, H.-W. Shen, and R. Crawfis. View point evaluation and streamline filtering for flow visualization. In *Proceedings of IEEE Pacific Visualization Symposium*, pages 83–90, 2011.
- [3] S. Marchesin, C.-K. Chen, C. Ho, and K.-L. Ma. View-dependent streamlines for 3D vector fields. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):1578–1586, 2010.
- [4] B. Moberts, A. Vilanova, and J. J. van Wijk. Evaluation of fiber clustering methods for diffusion tensor imaging. In *Proceedings of IEEE Visualization Conference*, pages 65–72, 2005.
- [5] M. Ruiz, I. Boada, M. Feixas, and M. Sbert. Viewpoint information channel for illustrative volume rendering. *Computers & Graphics*, 34(4):351–360, 2010.