

# An Illustrative Visualization Framework for 3D Vector Fields

Cheng-Kai Chen, Shi Yan, Hongfeng Yu, Nelson Max, Kwan-Liu Ma

By: Michael Tran

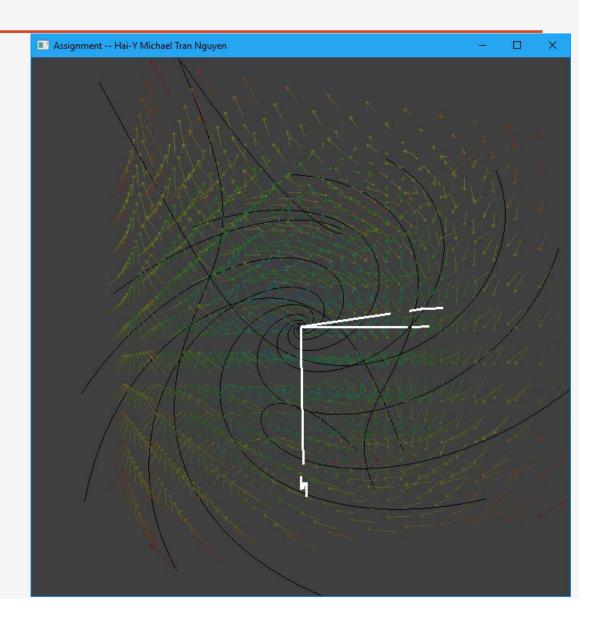
COSC 6344 – Visualization

11/30/2018

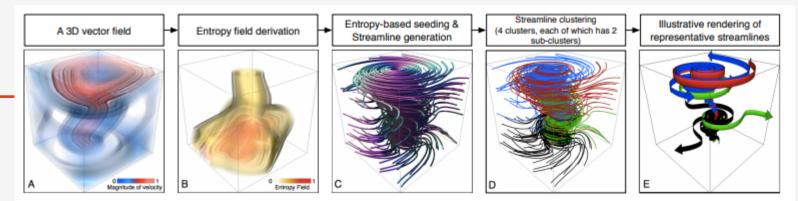
#### Goals

#### **Recall: Assignment 7...**

Instead of manually choosing seed locations or using stream/stream ribbon probes, we want to seed and visualize automatically.



#### Overview



Histogram/Binning, Entropy Calculations, Seeding

#### 2. Two-Stage Streamline Clustering

- K-means Algorithm on Vector Spatial Properties
- K-means Algorithm on Vector Shape Properties

#### 3. Streamtape Generation

1. Entropy-Based Seeding

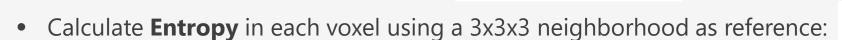
• Binormal Vector, Tangent Vectors, Normal Vectors, Torsion

## Entropy-Based Seeding

#### To calculate Entropy:

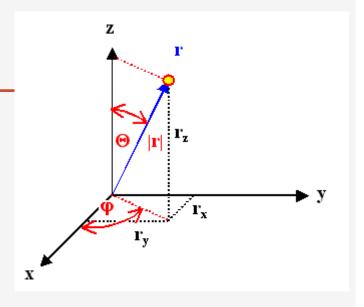
- Bin each voxel in the vector field depending on **Phi** ( $\varphi$ ) and **Theta** ( $\theta$ ).
- Calculate **Probability** in each voxel:

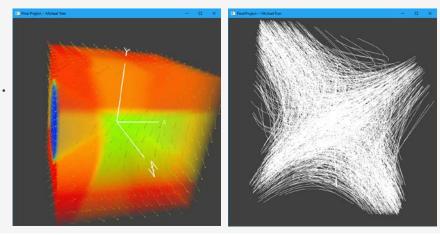
$$p(x_i) = \frac{C(x_i)}{\sum_{i=1}^n C(x_i)},$$



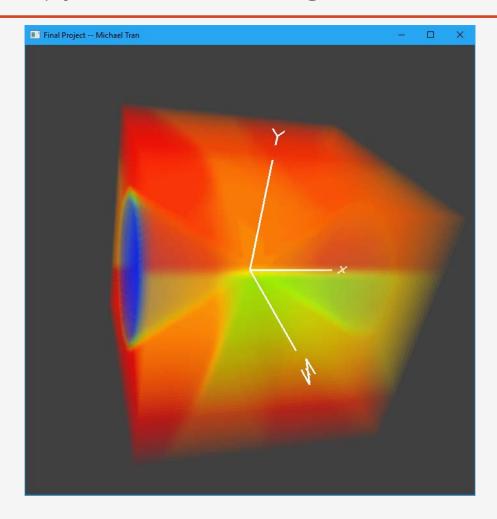
$$H(x) = -\sum_{x_i \in X} p(x_i) \log_2 p(x_i),$$

- Shuffle all points and choose 1000 random points
  - Give a point with higher entropy a higher chance of being chosen.

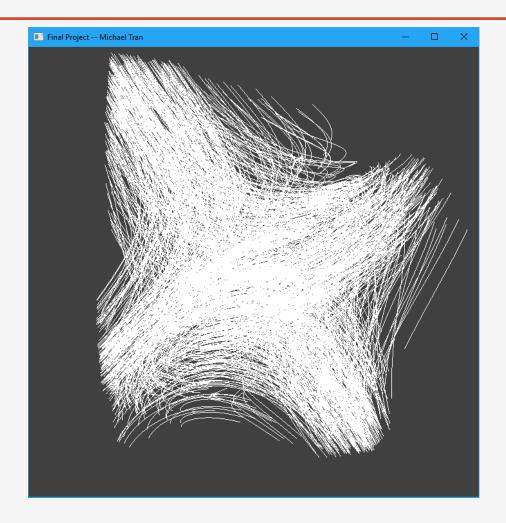




# Entropy-Based Seeding - Results



**Entropy Field** 

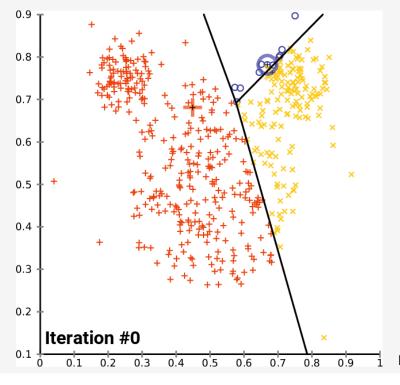


1000 Seeds Picked Based on Entropy Field

## Streamline Clustering

To cluster properly, we cluster **two times** – cluster all streamlines, and then cluster again on the clusters from the previous clustering.

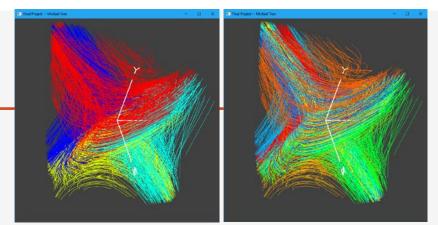
To cluster, we employ the k-means clustering algorithm based on certain vector properties.



https://en.wikipedia.org/wiki/K-means\_clustering

#### K-means Algorithm

First Stage: K-means Algorithm on Vector Spatial Properties

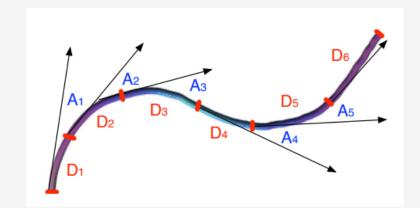


For the first clustering we take the streamline start/mid/end point as our clustering property.

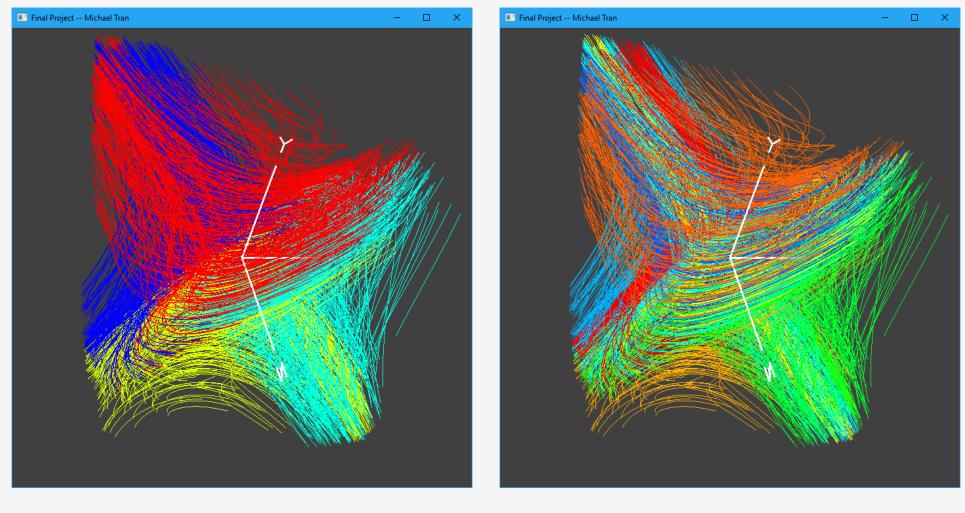
**Second Stage**: K-means Algorithm on Vector Shape Properties

• We take the clusters from the first stage and apply K-means algorithm again on each cluster. We use **Linear Entropy (EL)** and **Angular Entropy (EA)** as our clustering property.

$$E_L = -\frac{1}{\log_2(m+1)} \sum_{j=0}^m \frac{D_j}{L_S} \log_2 \frac{D_j}{L_S} \qquad E_A = -\frac{1}{\log_2(m)} \sum_{j=0}^{m-1} \frac{A_j}{L_A} \log_2 \frac{A_j}{L_A}$$



# Streamline Clustering - Results



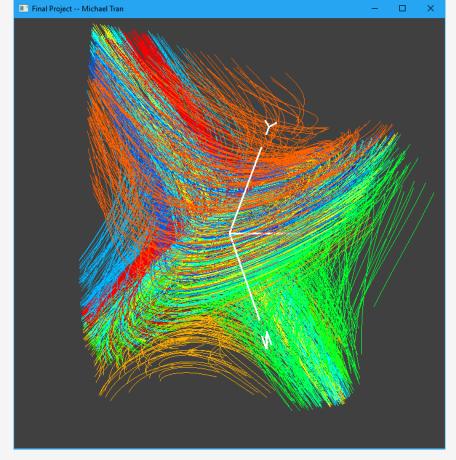
Stage 1 Clustering

Stage 2 Clustering

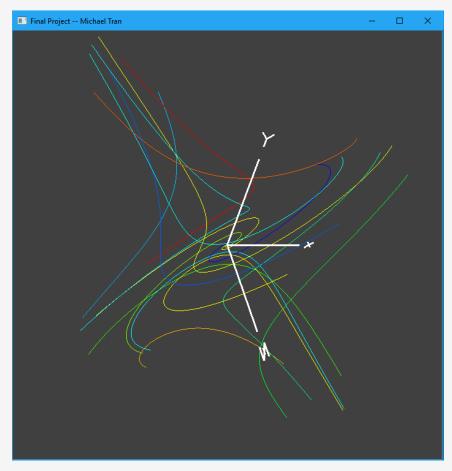
# Streamline Clustering – Bundling

After all streamlines are clustered, we pick the streamline closest to each centroid as the candidate

streamline.



Stage 2 - Clustering



**Bundled Streamlines** 

#### Streamtape Generation

At each point on a streamline, we calculate the following variables:

Binormal Vector **B**, Tangent Vector **V**, Normal Vector **N**, Torsion  $\tau$ , Width  $\omega$ 

$$\begin{array}{lcl} B & = & T \times N \\ T & = & dr/ds \\ N & = & dT/ds \end{array} \qquad \tau = \frac{det(r', r'', r''')}{||r' \times r''||^2} \qquad \omega = 1.0 - \tau.$$

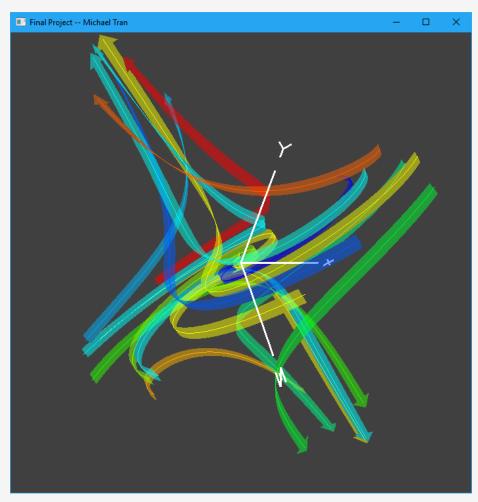
$$\tau = \frac{det(r', r'', r''')}{||r' \times r''||^2}$$

$$\omega = 1.0 - \tau.$$

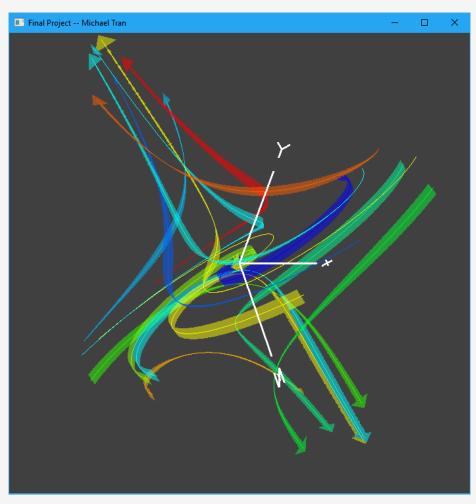
r', r", r"' are the first, second, and third derivatives of r(s) (the streamline).

Once we have the values, we can render the stream tape.

# Streamtape Generation - Results



Streamtapes (Without Factoring Torsion)



Streamtapes (With Torsion)

# Demo