A Trajectory Clustering Approach To Crowd Flow Segmentation in Videos

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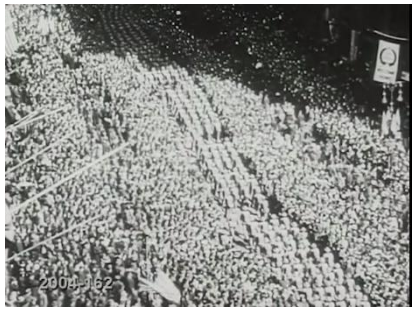
INTRODUCTION

Introduction






- World has seen various events of human loss due to crowd mismanagement.
  - 1954 Kumbh Mela stampede: 800+ killed, 2000+ injured.
  - 2005 Al-Aaimmah bridge stampede: 953 killed
- Existing object detection and tracking methods are not suitable for crowd scenes.
  - Complex dynamics of crowd scenes.
  - Large number of very small objects are difficult to track simultaneously.

Problem Statement

Problem Statement

Sample Video

Image with segmented crowd-flow patterns

- Assumptions: -
  - Video camera used is a static one.
  - Video has at least 100 frames.

Related Works

Related Works

I. Pixel Domain Approaches
- Ali et al. *CVPR, 2007*
  - Approach is inspired by fluid dynamics theory.
  - Used finite time Lyapunov exponent fields to detect the Lagrangian coherent structures.
  - Further used these Lagrangian coherent structures to locate flow boundaries.

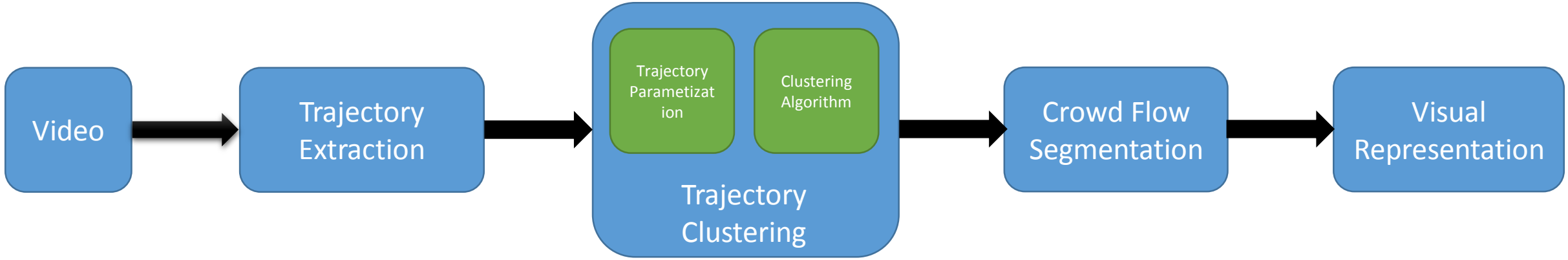
II. Compressed Domain Approaches
- Praveen et al. *IEEE CONECCT, 2014*
  - Used the standard expectation-maximization algorithm to cluster the motion vectors.
  - The clusters which converges to single flow are merged together.
- Kurthi et al. *IEEE ICIP, 2014*
  - Modelled the motion vectors as conditional random fields (CRF).
  - The crowd flow segments are obtained by labelling the motion vectors such that the global energy of the CRF is minimized.

- The above approaches do not take into account the temporal evolution of motion vectors but just rely on their average over time.

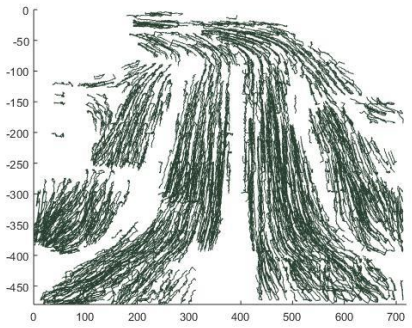
Methodology

Methodology

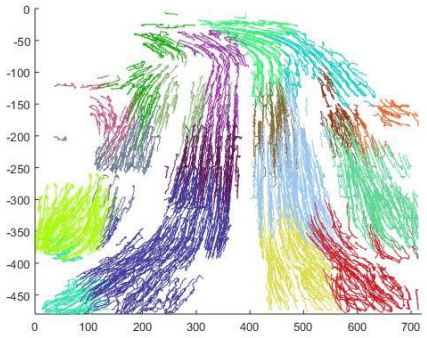
- Our approach is based on trajectory clustering.



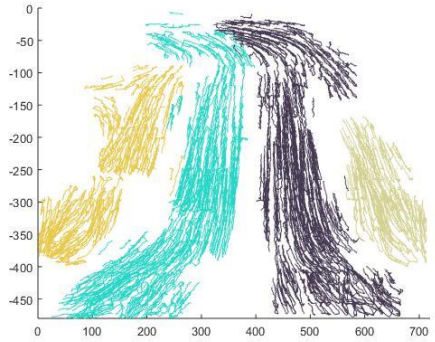
Sample Video



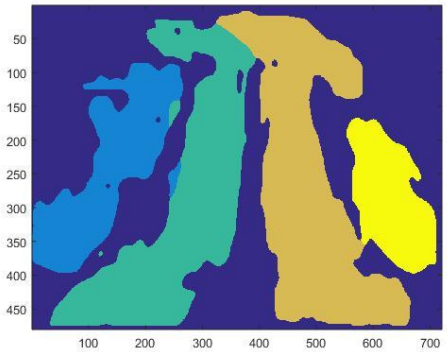
Extracted Trajectories



Clustered Trajectories



Final Flow Segmentations



Pixel-wise visualization

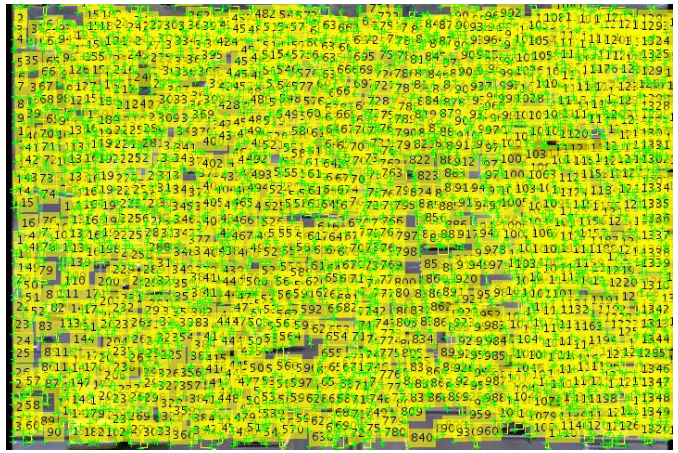
Trajectory Extraction

- Object detection and tracking is not practical for high density videos.
- We track mid-level structures, blocks [64x64].
- We use standard Lucas-Kanade-Tomasi[1] tracking algorithm to obtain the required trajectories.
- Tracker constituents are revised after every 40 frames to take into account the newly appearing objects.

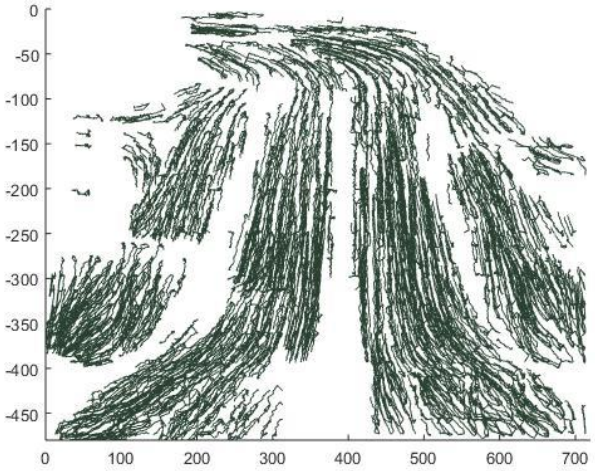
[1] Carlo Tomasi and Takeo Kanade. Detection and Tracking of Point Features. *Carnegie Mellon University Technical Report CMU-CS-91-132*, April 1991.

Trajectory Extraction

Sample Video



Tracking under process



Extracted Tracjectories

Trajectory Clustering

a. Trajectory representation
   I. Shape features: - Parameterizing the shape of the trajectories by expressing them as a polynomial function of time.
   II. Location features: - Takes into account the mean spatial location of a trajectory.
   III. Flow direction: - Takes care of the direction of flow of a trajectory with respect to the dominant flow direction of a video.
   IV. Density features: - Consider the information from the neighborhood of trajectories which is useful in segregating spatially overlapping clusters.

Trajectory Clustering

a. Trajectory clustering algorithm

Step1: - Representative *models* from different types of trajectory patterns are selected.

Step2 : - A binary matrix, called *Preference Set* is constructed.

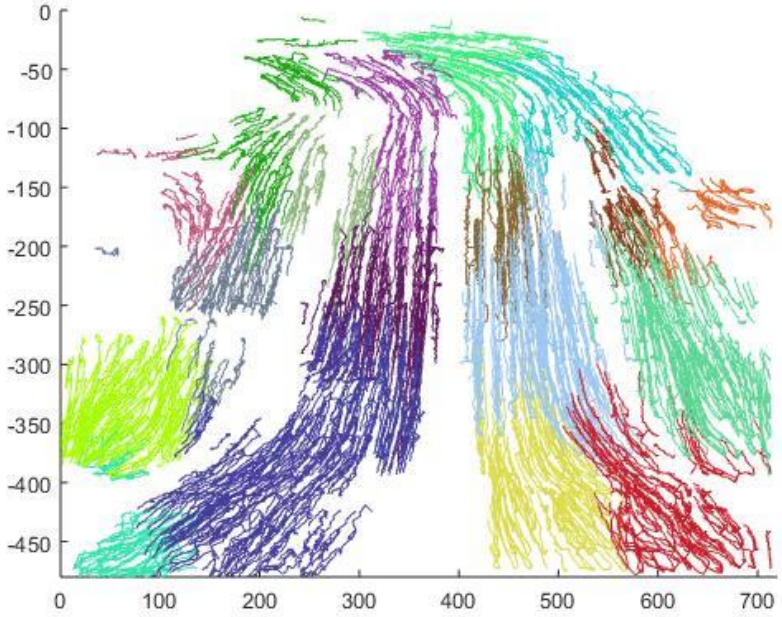
- *Preference Set* represents the vote of each trajectory to all models (1 for ‘match’, 0 otherwise).

Step3: -Using the Preference Set, an agglomerative clustering is performed.

- Jaccard distance is used as measure for similarity between two trajectories.

Trajectory Clustering

Sample Video

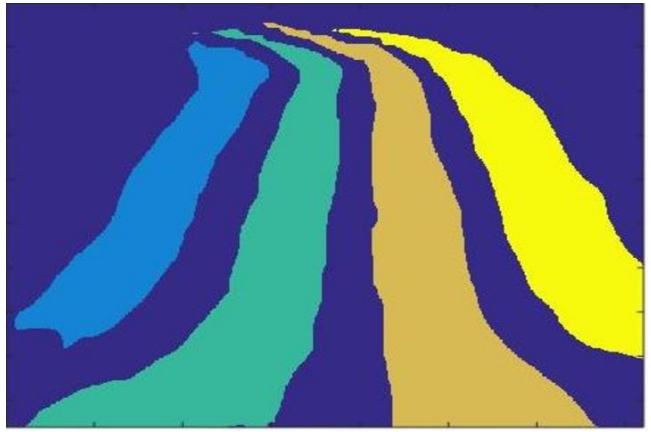


Clustering Results

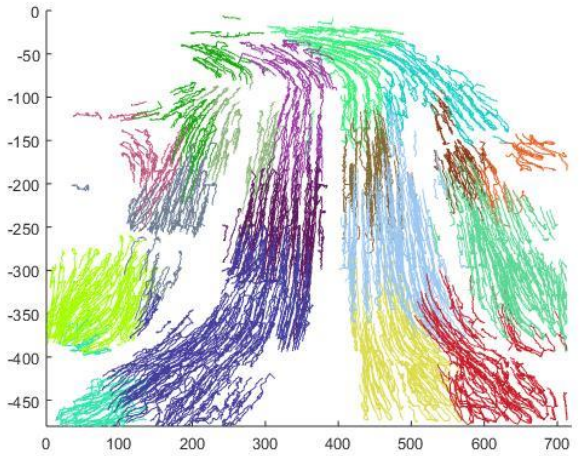
Crowd Flow Segmentation

- The mentioned trajectory clustering algorithm over-clusters the given set of trajectories.

Sample Video



Ground truth segmentation



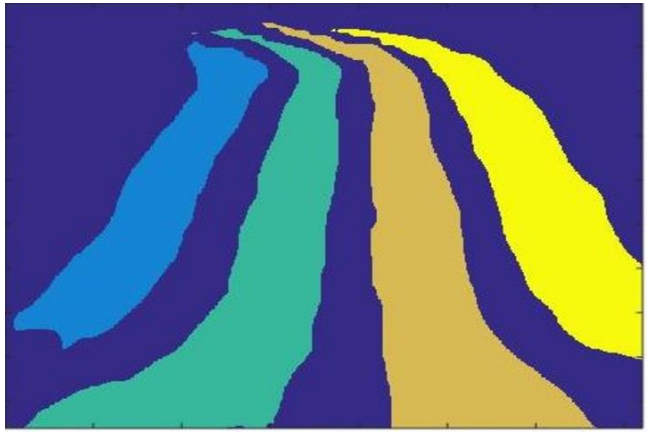
Clustering Results

- Objects belonging to same flow pattern may have different starting and terminating points in trajectories, thus may be structurally different.

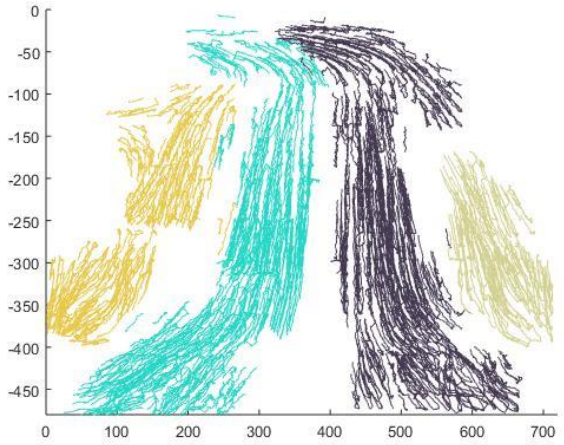
Crowd Flow Segmentation

- Using a slightly modified version of a density based clustering algorithm (DBSCAN [3]), we further perform a second round of clustering process over the previously obtained trajectory clusters.

Sample Video



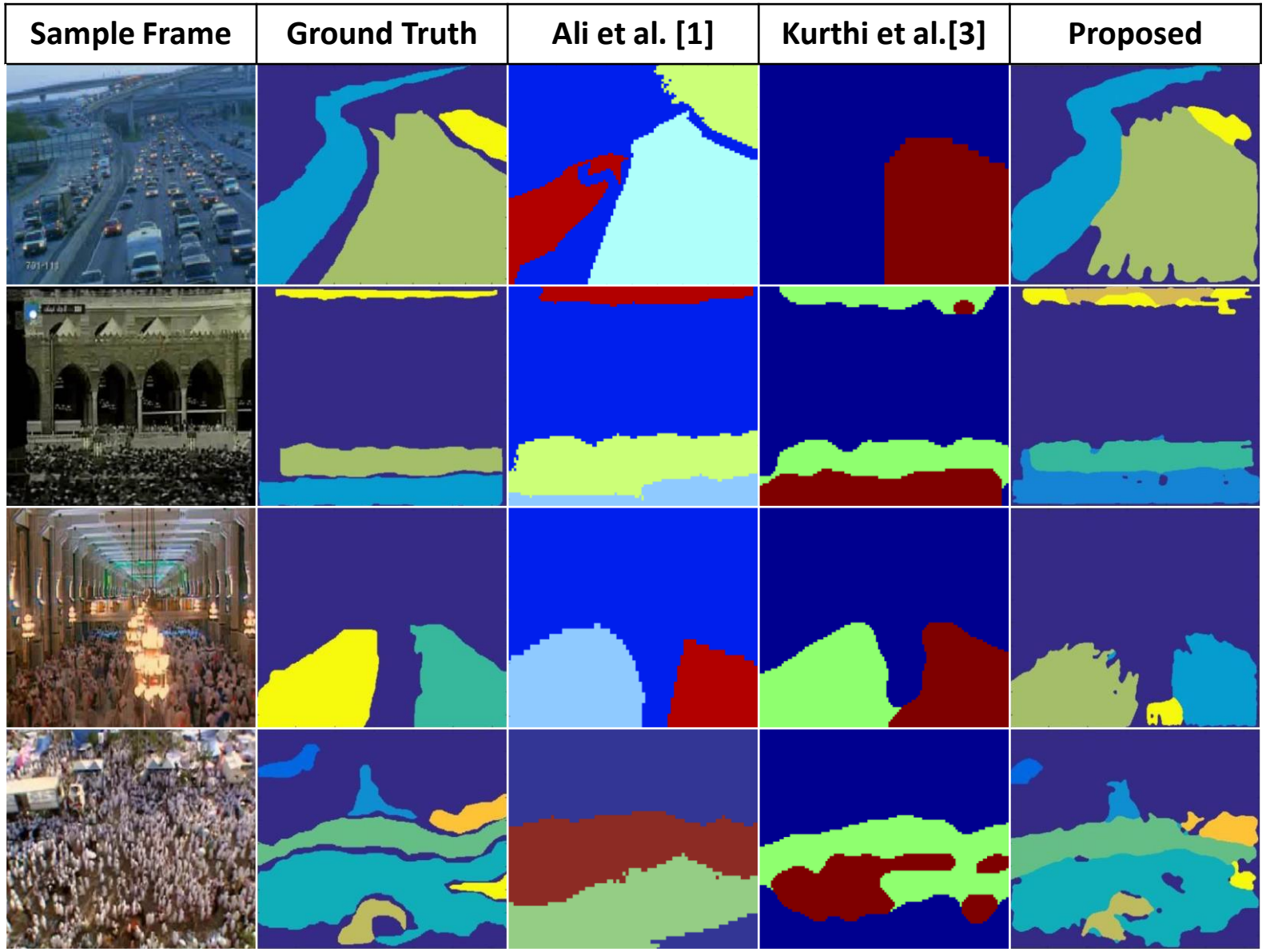
Ground truth segmentation



Final Crowd Flow Segments

Results

Results



Results

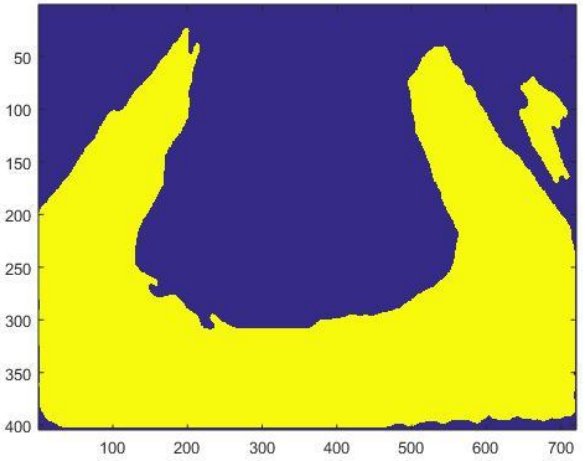
Test Samples	Ali et al.	Biswas et al.	Kurthi et al.	Proposed
Seq #1	0.72	0.25	0.92	**0.94**
Seq #2	0.68	0.64	0.47	**0.78**
Seq #3	0.56	**0.69**	0.61	0.66
Seq #4	0.74	0.70	**0.82**	0.76
Seq #5	0.42	0.57	0.40	**0.63**
Seq #6	0.47	**0.63**	**0.63**	0.51
Overall	0.60	0.58	0.64	**0.71**

Objective evaluation of segmentation performance measured in terms of Jaccard similarity with respect to the manually generated ground truth.

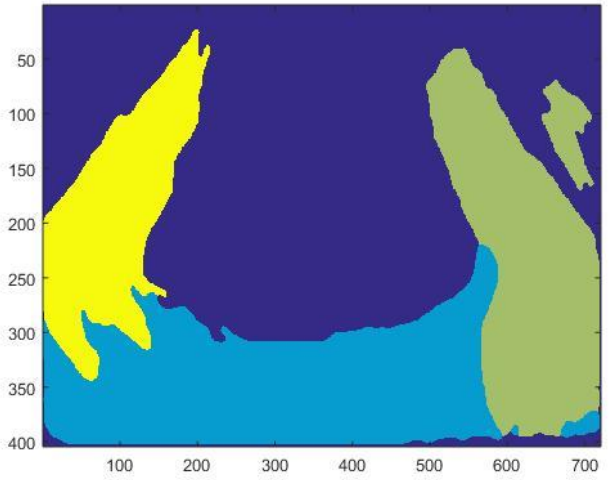
Limitations

- Over-clustering in cases if circular flows are present.

Sample Video



Ground Truth



Proposed Result

Conclusions

Conclusions

- Proposed an unsupervised approach to crowd flow segmentation.
- Proposed a new trajectory representation strategy, taking into account the shape, location, flow direction and density of trajectories.
- Developed a new trajectory clustering algorithm specific to high density scenarios.
- Demonstrated that our method can produce superior performance than state-of-the-art methods.

Contact Information

- For any queries, please contact the author.

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Thank You!!