Visual Surveillance for Dense Crowd Flow Analysis

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National Science Day 10th Research Scholars' Day 2020 IIT Bhubaneswar

Introduction

Large Gatherings in India

A crowd can be defined as a large number of people gathered together in an organized or disorganized way.
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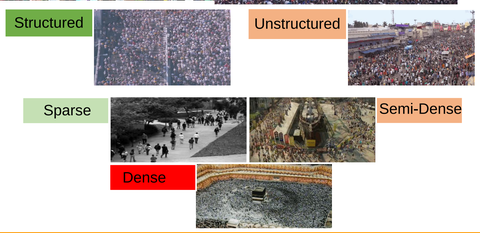


Manual Monitoring

Computer Vision-based Monitoring

- Less Human Efforts
- Better information fusion
- Prompt, Accurate & Intelligent
- Less processing time for huge volumes of videos

Motivation of Research

- Existing methods are restricted to be applicable to low and medium density crowd.
- These methods lack robustness in handling densely crowded scenarios.
- Literature [5] reveals that physics-based models describe crowd behavior to a greater extent. However, the available methods partially address the issues in densely crowded scenarios. Moreover, they are more complex in functionality and are computationally expensive.

Objectives

- Crowd flow segmentation using physics-based model.
- Crowd characterization and analysis using Computer-vision technique.
- Development of deep machine learning models for identification of different crowd behaviors.

Computer Vision + Physics-based models to understand Crowd behavior

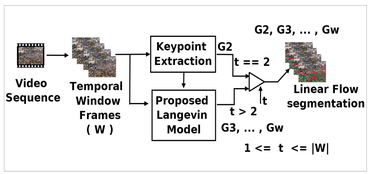
Understanding Crowd Flow behavior using Langevin Equation

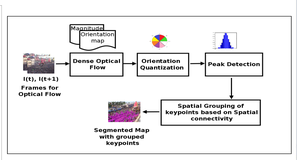
Passive Langevin Equation

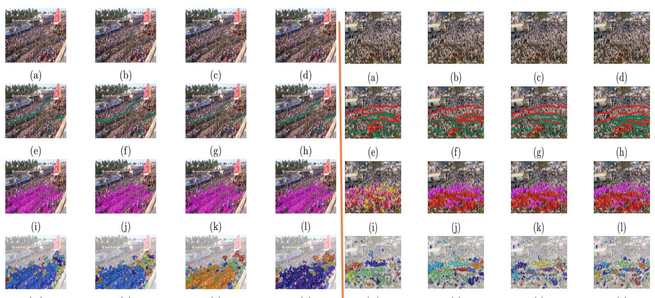
$$m_i \ddot{\vec{r}_i} = -\gamma \dot{\vec{r}_i} + \vec{F_i} + \vec{R_i}(t) \qquad F_{drift/confinement} = m \sum_i \frac{dv_i}{dt}$$

where r is the position of the particle, v_i the velocity of the particle, mass (m =1),

- F_i is drift force causing the particle to drift along x direction (a positive phenomenon), and F_i is a confinement force causing the particle to be confined along y direction (negative phenomenon).
- The random force ($R_i(t)$)is generated within (0- 1).

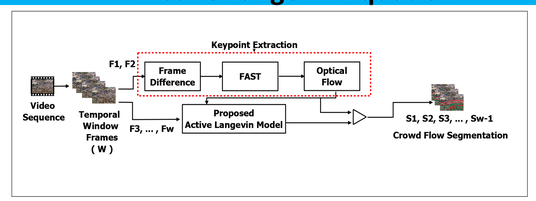






Segmentation Results: (a-d) Original recorded Frames (31-34) of the Rath Yatra video (LEFT) and (41-44) of the Fair Video (e-h) Ground Truth Frames, (i-l) represents segmented output obtained using proposed method and (m-p) represents output of segmentation method [1], respectively.

Active Langevin Equation



Proposed Active Langevin Model

$$F_{inertial} = F_{external} + F_{active} + F_{disturbance}$$

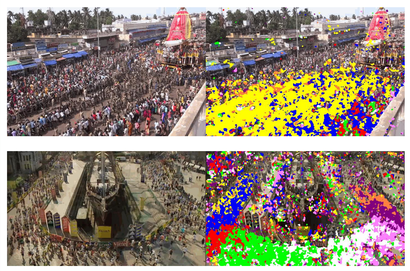
$$m_i \frac{\mathrm{d}v_{i,n}(t)}{\mathrm{d}t} = -\gamma v_{i,n}(t) + F_{active_{i,n}} + \xi(t), \qquad F_{active_{i,n}} = -\nabla U_{i,n} + F_{drift_{i,n}}$$

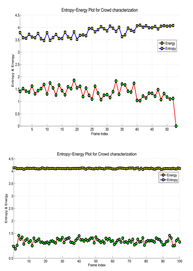
$$v_{new_{i,n}} = v_{old_{i,n}} - \gamma v_{new_{i,n}} \Delta t + F_{active} \Delta t + \xi(t) \Delta t$$

$$r_{new_{i,n}} = r_{old_{i,n}} + v_{new_{i,n}} \Delta t$$

(a-d) Original recorded Frames (61-64) of the Marathon-III video and (31-34) of the Rath Yatra Video (e-h) Ground Truth Frames, (i-l) represent segmented outputs obtained using method proposed in [4], (m-p) represent segmentation outputs of method [2], (q-t) represent segmentation outputs of method [3], and (u-x) represent segmentation outputs of the proposed method, respectively.

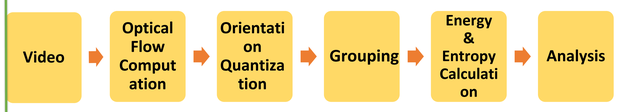
Crowd Characterization using Gibbs Entropy





Salient findings :

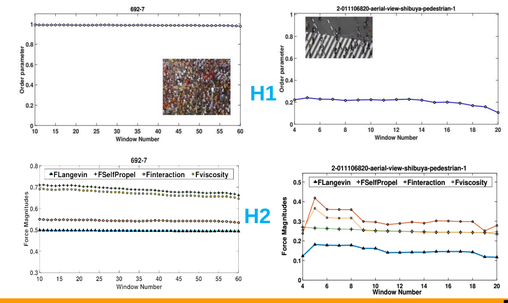
- Crowd dynamics in terms of *randomness and energy* computed with the help of *Gibbs entropy* and *Kinetic energy*
- If *significant fluctuations are observed in inter-frame energy*, they indicate a *fast moving crowd with higher velocity*.
- If the *fluctuations in inter-frame energy difference are low*, then the *crowd* can be assumed to be *moving at a uniform but lesser velocity*.
- Similarly, *more fluctuations in the entropy* curve indicate *varying randomness* in the crowd. For *constant entropy, the randomness can be assumed to be less* in a video.



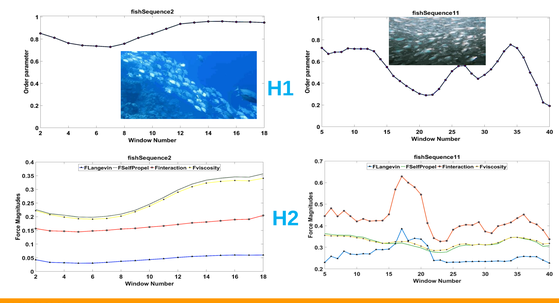
Crowd Characterization using Active Langevin Force

- Proposed crowd characterization model is based upon the active Langevin equation
- Hypotheses based on the order parameter and interaction force component of the proposed model, which are enlisted below.
  - H1: Order Parameter for a structured crowd should be high and low for an unstructured crowd.
  - H2: Interaction force should be less for structured crowd and more for an unstructured crowd.

Experimentation on Human Crowds



Experimentation on School of Fish



Conclusion and Future Works

The proposed Langevin-based models are simple in functionality and are able to describe human crowd movements more efficiently than other crowd movement models. The proposed models are computationally less expensive than existing state-of-the-art methods. The computer vision scheme based on Gibbs entropy is able to characterize crowd in terms of energy and randomness. The active Langevin model also characterizes crowd in terms of organization. Further, these models can be used to generate feature maps which can be used along with machine learning techniques to perform crowd anomaly detection in dense crowded scenarios.

Disseminations

- **S. Behera, D. P. Dogra, M. K. Bandyopadhyay and P. P. Roy. Estimation of Linear Motion in Dense Crowd Videos using Langevin Model, Experts Systems with Applications, Elsevier 21-FEB-2020 DOI information: 10.1016/j.eswa.2020.113333 .**
- **S. Behera, D. P. Dogra, and P. P. Roy. Characterization of Dense Crowd Using Gibbs Entropy. In Proceedings of 2nd International Conference on Computer Vision & Image Processing, IIT Roorkee, 2017 (pp. 289-300). Springer, Singapore.**
- **S. Behera, D. P. Dogra, M. K. Bandyopadhyay and P. P. Roy. Segmentation and Visualization of Crowd Flow in Videos using Hybrid Force Model, 2020 VISAPP, Malta.**

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1. Ali, S. and Shah, M. (2007). A lagrangian particle dynamics approach for crowd flow segmentation and stability analysis. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–6.
2. Kulkarni, A., Thampi, S.P., Panchagnula, M.V.: Sparse game changers restore collective motion in panicked human crowds. Physical review letters 122(4), 048002 (2019)
3. H. Ullah, M. Uzair, M. Ullah, A. Khan, A. Ahmad, W. Khan, Density independent hydrodynamics model for crowd coherency detection, Neurocomputing 242 (2017) 28-39.
4. Mahapatra, P.S., Kulkarni, A., Mathew, S., Panchagnula, M.V., Vedantam, S.: Transitions between multiple dynamical states in a confined dense active-particle system. Physical Review E 95(6), 062610 (2017) .
5. X. Zhang, Q. Yu, H. Yu, Physics inspired methods for crowd video surveillance and analysis: a survey, IEEE Access, 2018.

Acknowledgement: The authors would like to thank the Science and Engineering Research Board (SERB), Department of Science and Technology, Government of India for funding this research work through the grant YSS/2014/000046.