Crowd Scene Understanding with Coherent Recurrent Neural Networks

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Outline

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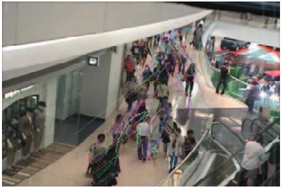

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- Avoiding Tragic Accidents

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- Obtain reliable tracklets from each scene using KLT trackers. At any time-instant t, the i^{th} person is represented by his/her coordinate $(\mathbf{x}_i(t), \mathbf{y}_i(t))$.

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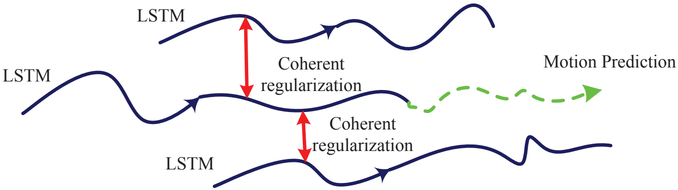
- Predict future trajectories of pedestrians and use extracted hidden features to do other classification tasks.



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- Crowd spatio-temporal patterns behave nonlinear dynamics
    - Limit cycles
    - Quasi-period
    - Chaos

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  - Limit cycles
  - Quasi-period
  - Chaos
- Collective effect (or coherent motion)
  - Pedestrian tend to form groups
  - Intra-group properties and inter-group properties.

Previous Work

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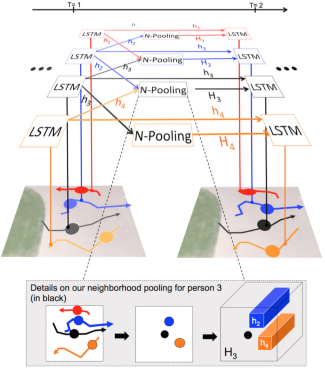
- Probabilistic Forecasting such as *Gaussian Process*
- Recurrent Neural Networks
  - N-LSTM (*CVPR* 2016)



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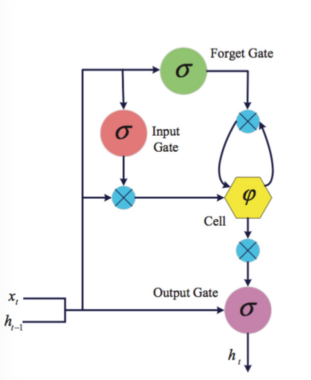
LSTM



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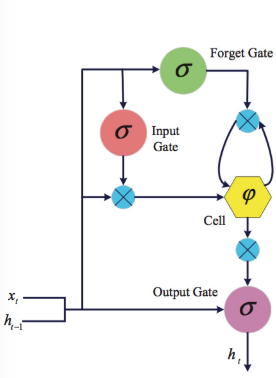

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  - Input / Output / Forget gate
  - Memory state $\mathbf{c}_t$

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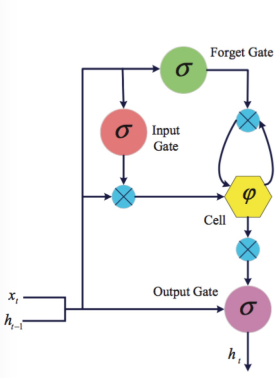

- Structure
  - Input / Output / Forget gate
  - Memory state $\mathbf{c}_t$
- Advantage
  - Prevent vanishing gradient problem
  - Nonlinear characteristic
  - Generalization

LSTM

$$\mathbf{i}_t = \sigma(\mathbf{W}_{xi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1} + \mathbf{W}_{ci}\mathbf{c}_{t-1} + \mathbf{b}_i) \tag{1}$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_{xf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1} + \mathbf{W}_{cf}\mathbf{c}_{t-1} + \mathbf{b}_f) \tag{2}$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_{xc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c) \tag{3}$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_{xo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1} + \mathbf{W}_{co}\mathbf{c}_t + \mathbf{b}_o) \tag{4}$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \tag{5}$$

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- The individuals are always willing to engage with “seed” groups and form spatially coherent structures.
- When the neighboring relationship of individuals remain invariant over time and correlation of their velocities remain high, they tend to have similar hidden state.
- The trajectories of pedestrians not only follow the *old* trend, but also are influenced by *current* environment.

cLSTM Unit

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \sum_{j \in \mathcal{N}} \lambda_j(t) \mathbf{f}_t^j \odot \mathbf{c}_{t-1}^j + \mathbf{i}_t \odot \tanh(\mathbf{W}_{xc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c) \tag{6}$$

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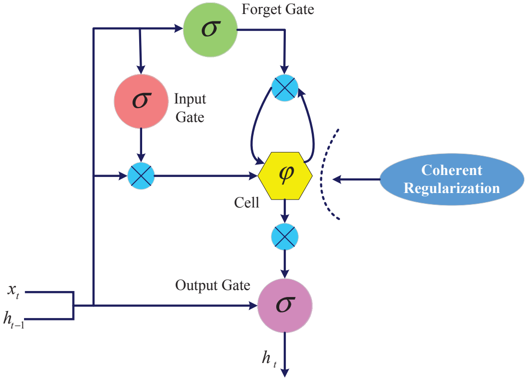

Coherent Motion Modeling

Use coherent filtering [Zhou et al., 2012a] [Shao et al., 2014] to discover the coherent group.

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The dependency relationship between two tracklets within the same group is measured as:

$$\tau_j(t) = \frac{\mathbf{v}_i(t) \cdot \mathbf{v}_j(t)}{\|\mathbf{v}_i(t)\| \|\mathbf{v}_j(t)\|} \tag{7}$$

Dependency Coefficient

The dependency coefficient between the i_{th} and j_{th} tracklets in Eq. (6) is defined as

$$\lambda_j(t) = \frac{1}{\mathbf{Z}_i} \exp\left(\frac{\tau_j(t) - 1}{2\sigma^2}\right) \in (0, 1], \tag{8}$$

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- $\lambda_j(t) \simeq 1$ if $\mathbf{v}_i(t) \simeq \mathbf{v}_j(t)$ which implies that tracklets i and j are similar.
- Coherent regularization encourages the tracklets to learn similar feature distributions by sharing information across tracklets within a coherent group.

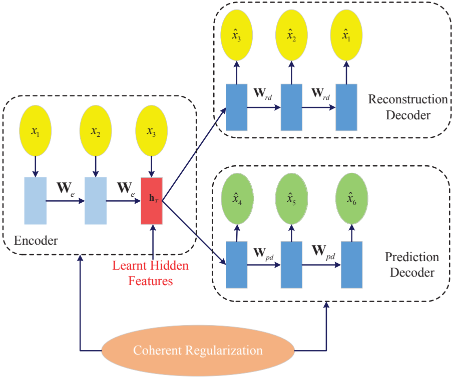
Framework

Unsupervised encoder-decoder cLSTM framework:

$$\mathbf{h}_T = cLSTM_e(\mathbf{x}_T, \mathbf{h}_{T-1}), \tag{9}$$

$$\hat{\mathbf{x}}_t = cLSTM_{dr}(\mathbf{h}_t, \hat{\mathbf{x}}_{t+1}), \text{ where } t \in [1, T], \tag{10}$$

$$\hat{\mathbf{x}}_t = cLSTM_{dp}(\mathbf{h}_t, \hat{\mathbf{x}}_{t-1}). \text{ where } t > T, \tag{11}$$



Crowd Scene Profiling

Solve critical tasks in crowd scene analysis:

- Estimating group state
  - *Gas, Solid, Pure Fluid and Impure Fluid*
  - Softmax classification using the feature learnt from the unsupervised cLSTM.

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- Crowd video classification

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Datasets and Settings

- CUHK Crowd Dataset
  - `http://www.ee.cuhk.edu.hk/~xgwang/CUHKcrowd.html`
  - Scene: streets, shopping malls, airports and parks
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- Settings
  - 128 hidden units in cLSTM
  - 2/3 of tracklets as the input and 1/3 as the predicted tracklets to evaluate the performance.

Future Path Forecasting

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Table 1: Error of Path Prediction(pixels)

Kalman Filter	Un-coherent LSTM	Coherent LSTM
9.32 ± 1.99	6.64 ± 1.76	4.37 ± 0.93

Group State Estimation

- Gas: Particles move in different directions without forming collective behaviors
- Solid: Particles move in the same direction with relative positions unchanged
- Pure Fluid: Particles move towards the same direction with ever-changing relative positions
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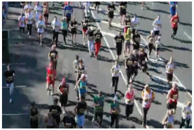
(a) Gas

(b) Solid

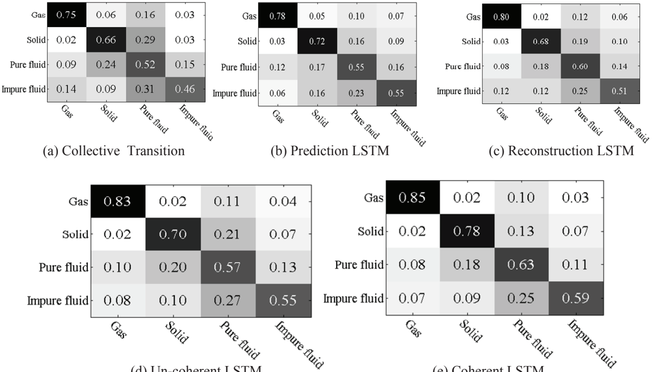


(c) Pure Fluid

(d) Impure Fluid

Group State Estimation

Confusion matrices of estimating group states using different methods: (a) collective transition [Shao et al., 2014]; (b) prediction LSTM; (c) reconstruction LSTM; (d) un-coherent LSTM; and (e) coherent LSTM.



(a) Collective Transition (b) Prediction LSTM (c) Reconstruction LSTM

(d) Un-coherent LSTM (e) Coherent LSTM

Crowd Video Classification

All video clips are annotated into 8 classes as 1) *Highly mixed pedestrian walking*; 2) *Crowd walking following a mainstream and well organized*; 3) *Crowd walking following a mainstream but poorly organized*; 4) *Crowd merge*; 5) *Crowd split*; 6) *Crowd crossing in opposite directions*; 7) *Intervened escalator traffic*; and 8) *Smooth escalator traffic.*

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	1	2	3	4	5	6	7	8
1	0.72	0.05	0.08	0.02	0.02	0.07	0.04	0.00
2	0.00	0.96	0.01	0.00	0.00	0.02	0.00	0.01
3	0.08	0.14	0.56	0.00	0.00	0.10	0.08	0.04
4	0.00	0.06	0.03	0.82	0.00	0.04	0.05	0.00
5	0.05	0.08	0.08	0.00	0.67	0.07	0.05	0.00
6	0.00	0.06	0.05	0.00	0.00	0.81	0.04	0.04
7	0.00	0.10	0.05	0.02	0.04	0.02	0.75	0.02
8	0.00	0.03	0.00	0.00	0.04	0.00	0.03	0.90

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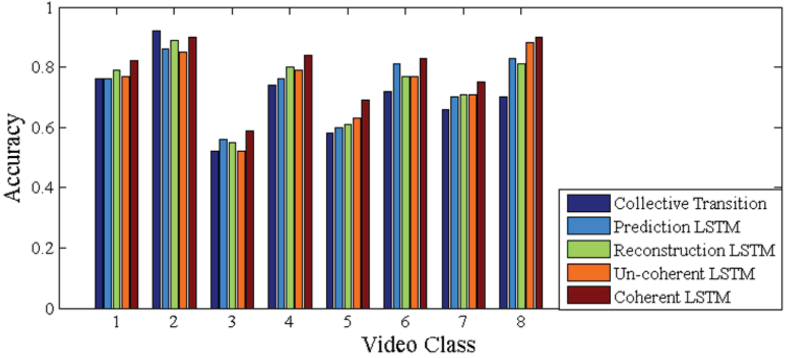

Thanks for your time!

Questions?