Crowd Scene Understanding with Coherent Recurrent Neural Networks

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Outline

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1. Introduction
2. LSTM Recap
3. Coherent LSTM
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Background

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- In the real scenes, pedestrians tend to form groups and their trajectories are influenced by others and obstacles.
- The main challenges of crowd motion analysis are *nonlinear dynamics* and *coherent motion*.

Problem Formulation

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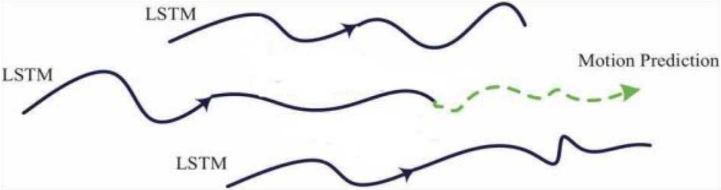
- Predict future trajectories of pedestrians and use extracted hidden features to recognize crowd motions.



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  - Optimize *energy function*
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- Probabilistic Forecasting
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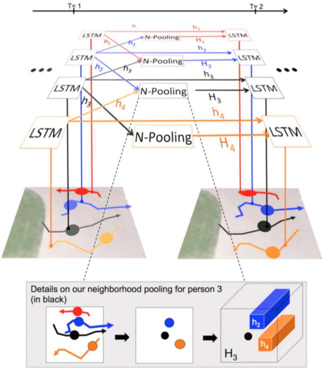
- Recurrent Neural Networks
  - N-LSTM [Alahi et al., 2016]



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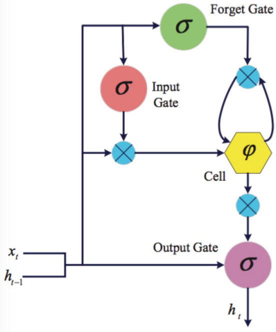
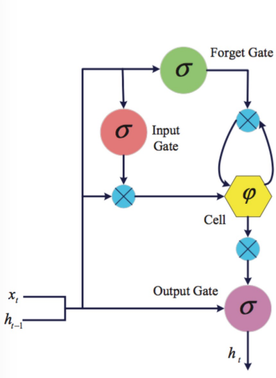
LSTM



LSTM



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

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

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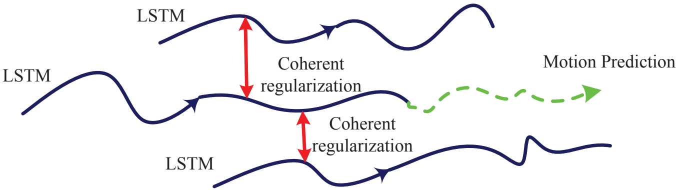
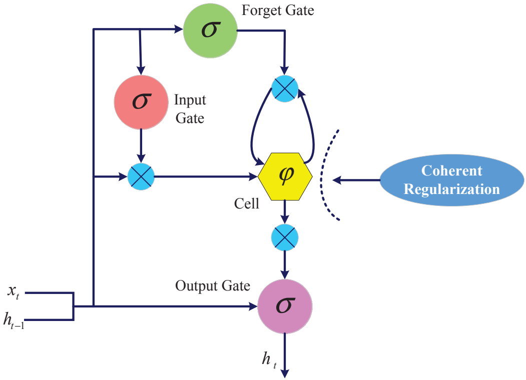
- LSTM can model individual behaviors but can't capture the interaction in a group.
- When the neighboring relationship of individuals remain invariant over time and correlation of their velocities remain high, they tend to have similar hidden state.
- The trajectories of pedestrians not only follow the *old* trend, but also are influenced by *current* environment.



cLSTM Unit

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_{xc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1} + \mathbf{b}_c) + \sum_{j \in \mathcal{N}} \lambda_j(t)\mathbf{f}_t^j \odot \mathbf{c}_{t-1}^j \tag{2}$$



Coherent Motion Modeling

Use coherent filtering [Zhou et al., 2012] [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:

$$\tau_j(t) = \frac{\mathbf{v}_i(t) \cdot \mathbf{v}_j(t)}{\|\mathbf{v}_i(t)\|\|\mathbf{v}_j(t)\|} \tag{3}$$

Dependency Coefficient

The dependency coefficient between the i_{th} and j_{th} tracklets in Eq. (2) is defined as

$$\lambda_j(t) = \frac{1}{\mathbf{Z}_i} \exp\left(\frac{\tau_j(t) - 1}{2\sigma^2}\right) \in (0, 1] \tag{4}$$

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- $\mathbf{Z}_i$: normalization constant corresponding to the i_{th} tracklet.
- $\lambda_j(t) \simeq \mathbf{Z}_i^{-1}$ 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.

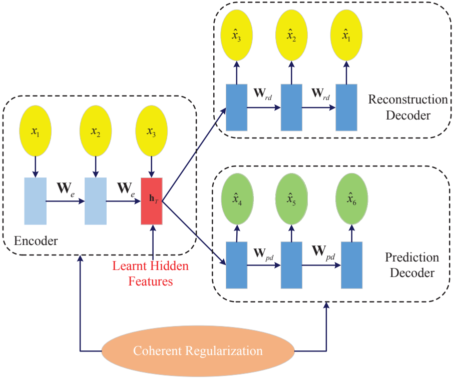
Framework

Unsupervised encoder-decoder cLSTM framework:

$$\mathbf{h}_T = cLSTM_e(\mathbf{x}_T, \mathbf{h}_{T-1}), \tag{5}$$

$$\hat{\mathbf{x}}_t = cLSTM_{dr}(\mathbf{h}_t, \hat{\mathbf{x}}_{t+1}), \text{ where } t \in [1, T], \tag{6}$$

$$\hat{\mathbf{x}}_t = cLSTM_{dp}(\mathbf{h}_t, \hat{\mathbf{x}}_{t-1}). \text{ where } t > T, \tag{7}$$



Crowd Scene Profiling

- Solve critical tasks in crowd scene analysis:
  - Group state estimation
  - Crowd video classification
- Softmax classification using the feature learnt from the unsupervised cLSTM.

Outline

Datasets and Settings

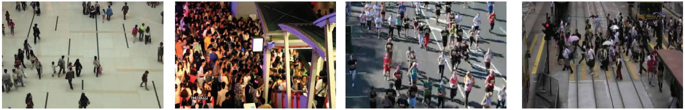
- CUHK Crowd Dataset
  - `http://www.ee.cuhk.edu.hk/~xgwang/CUHKcrowd.html`
  - Scene: streets, shopping malls, airports and parks
  - More than 400 sequences and more then 200,000 traklets
- Settings
  - 128 hidden units in cLSTM
  - 2/3 of tracklets as the input and 1/3 as the predicted tracklets to evaluate the performance.

Future Path Forecasting

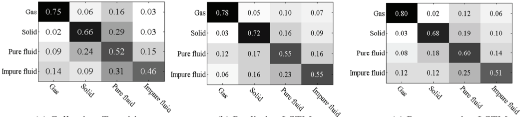
Table 1: Error of Path Prediction(pixels)

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

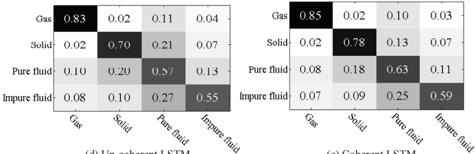
Group State Estimation



(a) Gas (b) Solid (c) Pure Fluid (d) Impure Fluid



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

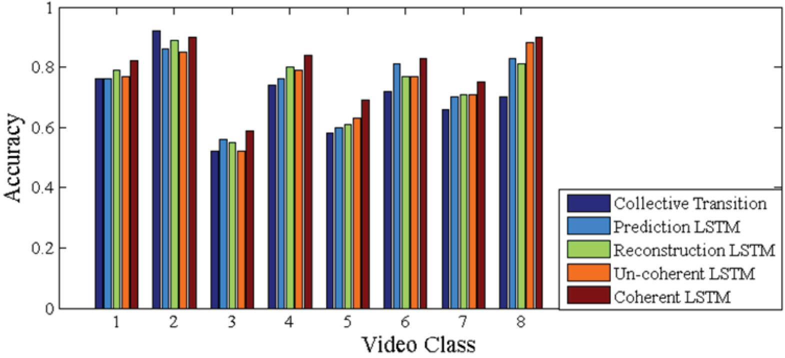


(d) Un-coherent LSTM (e) Coherent LSTM

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.

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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Conclusion

- A novel recurrent neural network with **coherent long short term memory unit**;
- Introduce a **coherent regularization** to consider the collective properties;
- **Outperform other methods** in group state estimation and crowd video classification.

Thanks for your time!

Questions?