





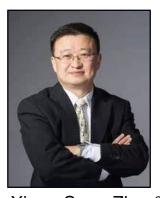
Forecasting Human Trajectory from Scene History















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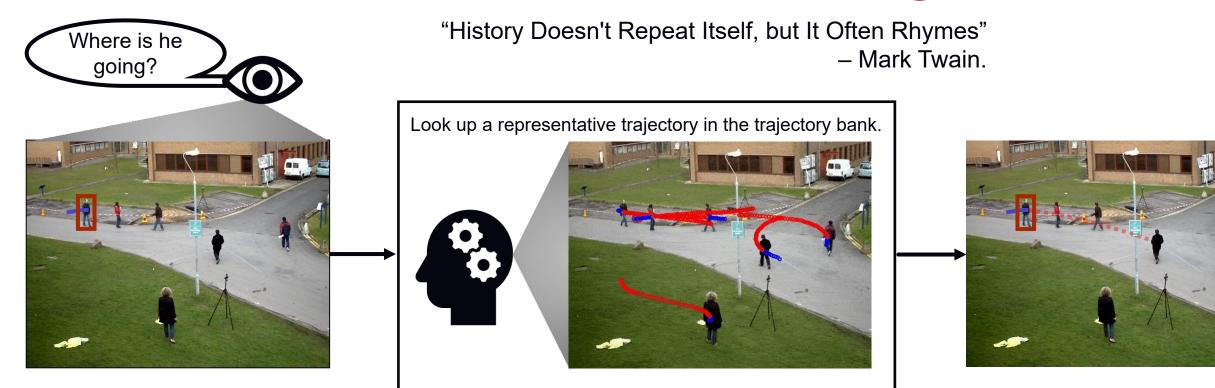
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Background







Human trajectory prediction (HTP)

Introduction

- Predicting a target person's future path from a video clip.
- Applied in many intelligent systems, including autonomous vehicles, care robots, and surveillance systems.

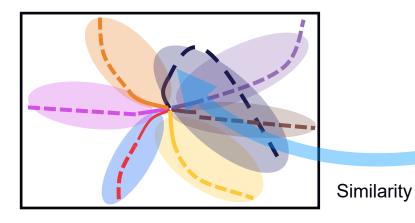
Challenge & Motivation

- Randomness and subjectivity of human movement (e.g., abrupt and sharp turns))
- The moving patterns of human in a constrained scenario typically conform to a limited number of regularities.

Introduction











Historical group trajectories

Observation

Surroundings

Main ideas

Since a person's subsequent trajectory has likely been traveled by others, we design a group trajectory bank module to extract representative group trajectories as the candidate for future path.

01.

02.

The moving patterns of human are constrained by the current scenario, thus we propose a cross-modal interaction module to model the interaction between individual past trajectory and its surroundings.

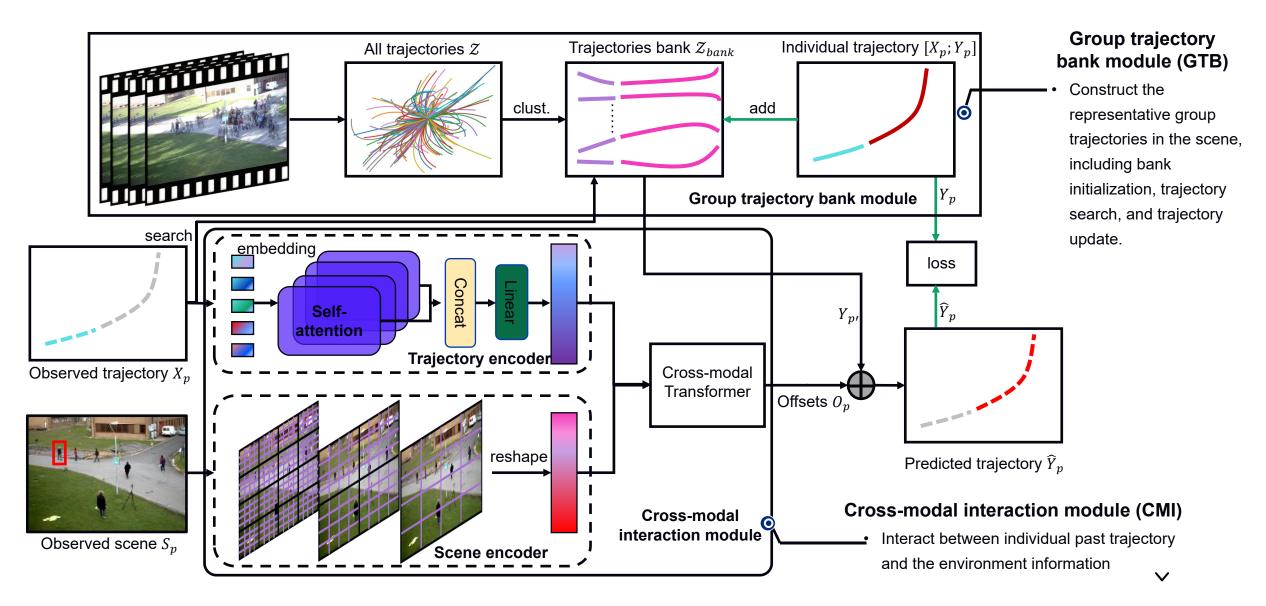
03.

To alleviate the uncertainty from randomness and subjectivity, we introduce curve smoothing (CS) into current evaluation metrics. Finally, We validate the efficacy of our framework on common benchmarks.





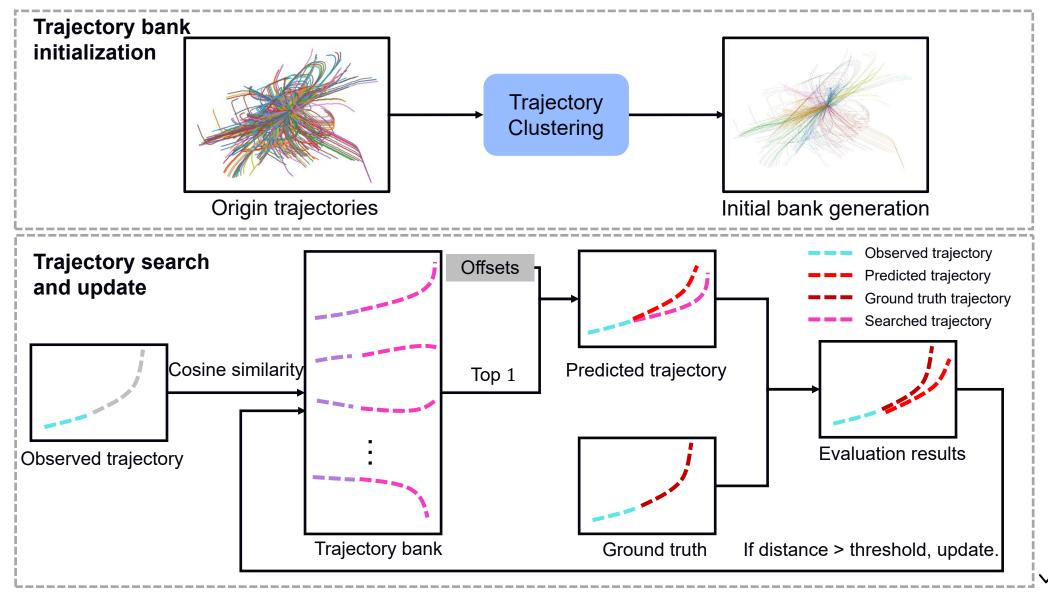




Method



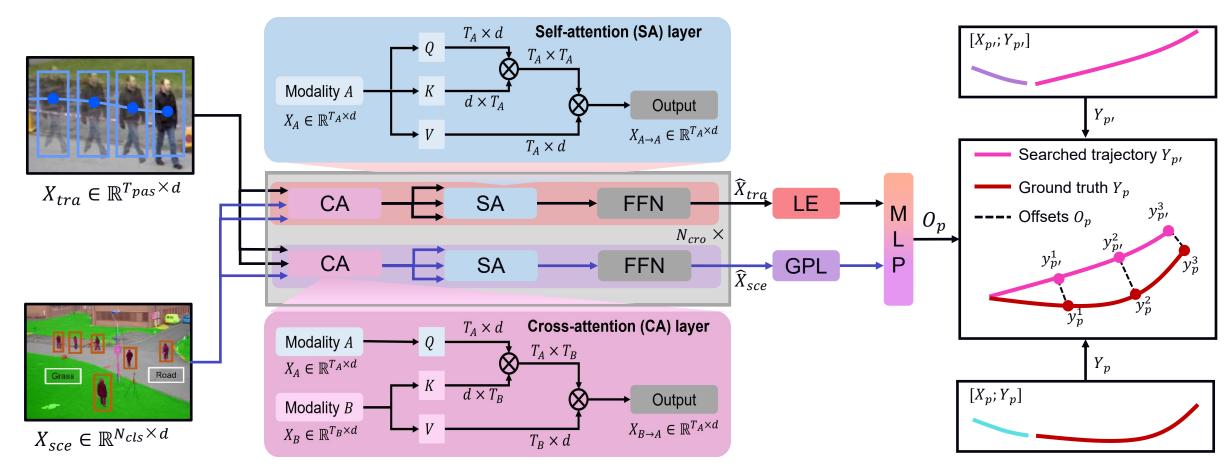




Method







An illustration of cross-modal transformer. The trajectory features and scene features are fed into the cross-modal transformer to learn the offsets between the searched trajectory and the ground-truth trajectory.





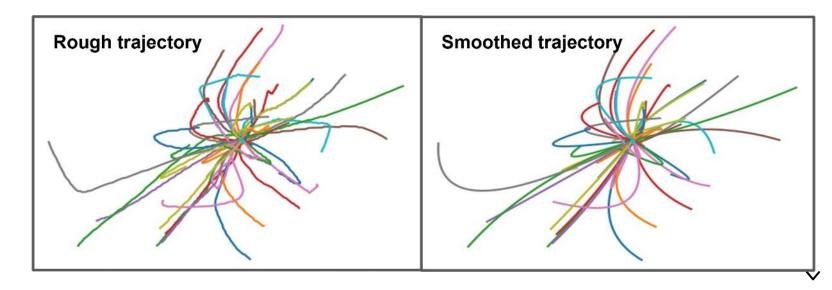
The illustration of our proposed metrics, CS-ADE and CS-FDE.

Predicted trajectory

Rough trajectory

Smoothed trajectory \hat{y}_p^1 \hat{y}_p^2 \hat{y}_p^2 \hat{y}_p^3 \hat{y}_p^3

Visualization of some samples after curve smoothing.



Results





Comparison of SOTA methods on PAV dataset.

Made ad	Evaluation metrics: CS-ADE↓ / CS-FDE↓ (in pixels)					
Method	PETS	ADL	VENICE	AVG		
SS-LSTM (WACV'18)	39.42 / 107.24	16.52 / 50.40	10.37 / 23.63	22.10 / 60.42		
Social-STGCN (CVPR'20)	43.40 / 117.85	24.34 / 57.22	14.42 / 38.66	27.39 / 71.24		
Next (CVPR'19)	37.54 / 98.56	16.82 / 46.39	8.37 / 19.32	20.91 / 54.76		
MANTRA (CVPR'20)	39.05 / 106.89	17.26 / 50.64	12.50 / 29.08	22.94 / 62.20		
Ynet (ICCV'21)	36.46 / <u>93.53</u>	<u>15.07</u> / <u>41.64</u>	7.10 / 16.11	<u>19.54</u> / <u>50.43</u>		
SHENet (Ours)	34.49 78.40	14.42 / 38.67	<u>7.76</u> / <u>18.31</u>	18.89 / 45.13		

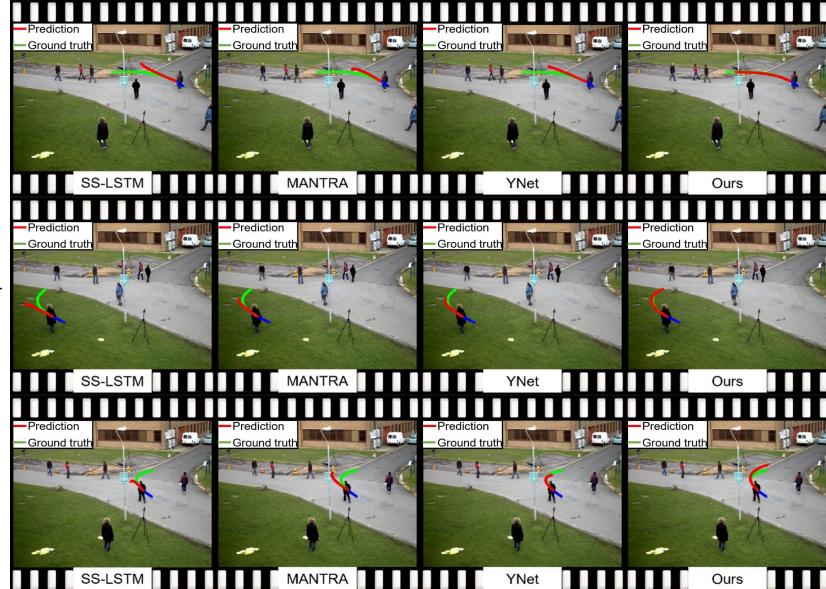
Comparison of SOTA methods on ETH/UCY datasets.

Method	Evaluation metrics: ADE↓ / FDE↓ (in meters)						
	ETH	HOTEL	UNIV	ZARA1	ZARA2	AVG	
SS-LSTM (WACV'18)	1.01 / 1.94	0.60 / 1.34	0.71 / 1.52	0.41 / 0.89	0.31 / 0.68	0.61 / 1.27	
Social-STGCN (CVPR'20)	0.75 / 1.38	0.61 / 1.40	0.58 / 1.03	0.42 / 0.70	0.43 / 0.71	0.56 / 1.05	
MANTRA (CVPR'20)	0.70 / 1.76	0.28 / 0.68	0.51 / 1.26	0.25 / 0.67	0.20 / 0.54	0.39 / 0.98	
AgentFormer (ICCV'21)	0.52 / 0.84	0.15 / 0.22	0.34 / 0.72	0.18 / <u>0.33</u>	<u>0.16</u> / 0.30	0.27 / 0.48	
Ynet (ICCV'21)	0.47 / 0.72	0.12 / 0.18	0.27 / 0.47	0.20 / 0.34	0.15 / 0.24	0.24 / 0.39	
SHENet (Ours)	0.41 / 0.61	0.13 / 0.20	0.25 / 0.43	0.21 / 0.32	0.15 / <u>0.26</u>	0.23 / 0.36	

Results





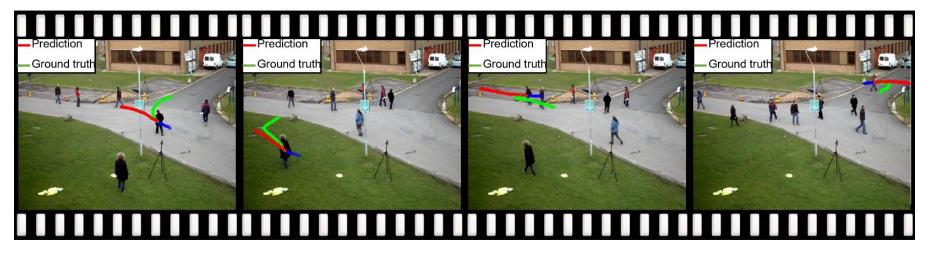


Qualitative visualization of our method and SOTA methods.

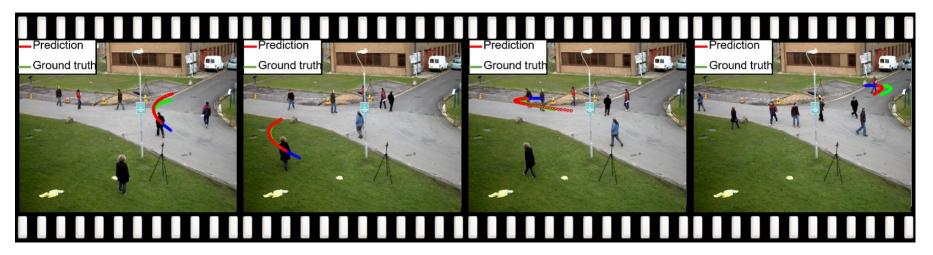
Results







Results without curve smoothing



Results with curve smoothing

Conclusion





A novel method that fully utilizes scene history for human trajectory prediction.



Please check our project page for more details: https://github.com/MaKaRuiNah/SHENet