Supplementary Material for CoMoGCN: Coherent Motion Aware Trajectory Prediction with Graph Representation

Yuying Chen*
ychenco@connect.ust.hk
Congcong Liu*
cliubh@connect.ust.hk
Bertram E. Shi
eebert@ust.hk
Ming Liu
eelium@ust.hk

Robotics Institute
Hong Kong University of Science and Technology
Hong Kong, China

1 Coherent motion clustering

1.1 Parameters for coherent motion clustering

Table 1 shows the parameters used for coherent filtering (CF) as well as DBSCAN. The Coherent Filtering methods are sensitive to the parameters chosen which are carefully tuned for each dataset. As coherent filtering can easily detect coherent motions in dense environments and induce false positives, we set a larger frame window size to ensure accuracy. Besides, the angular difference is limited to a smaller value for DBSCAN for accurate detection. The typical DBSCAN applies euclidean distance as the distance function. However, we considered the angular distance, lateral distance as well as longitudinal distance for better coherent motion clustering.

Dataset	coherent filtering			DBSCAN			
	d+2	$K_{\max}$	λ	θ	s_{lateral}	$s_{\text{longitudinal}}$	minPts
ETH, HOTEL, ZARA1, ZARA2	5	5	0.8	0.5	2	5	2
UNIV	8	5	0.8	0.2	2	5	2

Table 1: Parameters used for coherent motion clustering. d+2 frames indicates the frame window size. $K_{\max}$ indicates the maximum number of nearest neighbors. The coherent filtering considers K nearest neighbors. We set $K = min(K_{\max},$ Neighborhood size$)$. λ is the threshold. θ is the angle distance and the unit is radian. s_{lateral} is the lateral distance of the potential neighbors to the pedestrian considered. $s_{\text{longitudinal}}$ is the longitudinal distance. The unit is meter. minPts is the minimum points.

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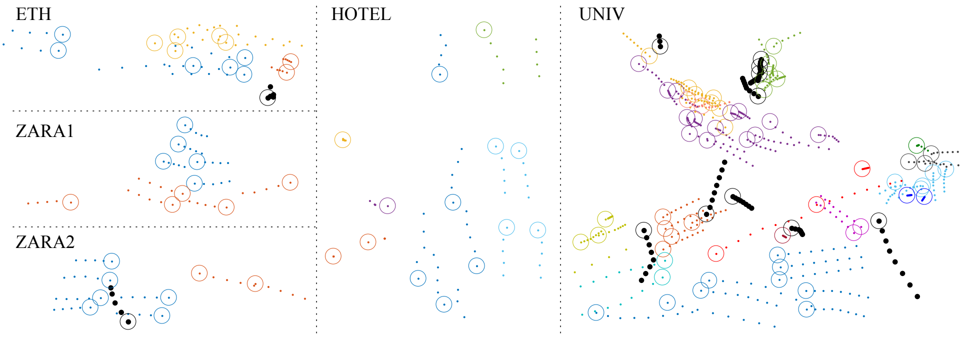

Figure 1: Representative examples and coherent motion clustering results for five datasets. Same color denotes the same group. Black color denotes individual that has no coherence with others. Circles show the current position and dots show the trajectory history used for clustering. We can see that coherent motions for both group of humans and individual humans are detected. Best viewed in color.

1.2 Coherence detection results

Typical examples of the coherent motion detection for each dataset can be seen in Fig. 1. We can see good performance of the coherent motion detection.

Fig. 2 shows the comparison of coherent motion detection between coherent filtering [2] and ours (leveraging DBSCAN clustering to compensate the drawback of coherent filtering). The clustering results clearly demonstrate the performance of coherent filtering being applied to the trajectory datasets. It performed well for detecting some coherent motions in dense crowds despite the difference in the motion directions and the space separations. However, it showed poor performance for detecting coherence in sparse trajectory datasets that consist of small groups. It can be observed that pedestrians with similar moving pattern are labeled as with no coherent motion when the number of coherent pedestrians is small. This caused the low labeling rate shown in Table 2, e.g. in the dataset HOTEL, of all the motions, only around 10% are labeled as coherent motions. Besides, some static pedestrians are mis-labeled (Fig. 2b) and become false positives for some clusters.

To compensate, we applied the DBSCAN to detect the small pedestrian clusters. As shown in Fig. 2, small group of pedestrians with similar moving directions are detected and labeled as the same motion cluster. Through this, the percentages of labeled coherent motions over all motions were increased to a reasonable value. To better show the improvement of the clustering methods, we compared the Fréchet distance [1] of trajectory pairs of inter or intra groups clustered by coherent filtering alone or with DBSCAN. The results are shown in Table 3. We can observe that with better coherence clustering on small groups, the Fréchet distance of coherent trajectories classified by coherent filtering and DBSCAN becomes smaller and it becomes larger for trajectories with little coherence. A lower Fréchet distance of two trajectories denotes higher similarity. It indicates improved coherence clustering of our proposed clustering method.

Dataset	CF	CF + DBSCAN
ETH	41.0%	77.3%
HOTEL	12.4%	77.6%
UNIV	35.0%	80.6%
ZARA1	38.9%	83.9%
ZARA2	45.6%	89.1%

Table 2: Percentage of labeled coherent motions over all motions.

Dataset	coherent filtering		coherent filtering + DBSCAN	
	Intra Group	Inter Group	Intra Group	Inter Group
ETH	3.58	7.30	3.21	8.59
HOTEL	4.10	5.08	2.90	5.69
UNIV	2.82	7.28	2.54	7.67
ZARA1	3.60	5.59	2.73	7.64
ZARA2	3.57	5.37	1.70	6.06
AVG	3.53	6.12	2.62	7.13

Table 3: Similarity of intra group trajectories and inter group trajectories for the two coherent detection methods. Here we use Fréchet distance to measure the similarity between trajectories.

2 Qualitative results of the ablation study for trajectory prediction

Figure 3 shows pedestrian trajectory prediction results for different models. We can observe consistent results with the quantitative evaluation. When compared to S-GAN, we can see that our models often generate more accurate and efficient predictions with lower variance in the case of interactions. We also observed that model using MLP tested in dataset HOTEL and UNIV tends to predict slower motion of humans than the real situations, which is similar to the performance of S-GAN. Among our models, we can see the proposed full model make more accurate and realistic predictions.

References

[1] Jiang Bian, Dayong Tian, Yuanyan Tang, and Dacheng Tao. A survey on trajectory clustering analysis. *arXiv preprint arXiv:1802.06971*, 2018.

[2] Bolei Zhou, Xiaoou Tang, and Xiaogang Wang. Coherent filtering: Detecting coherent motions from crowd clutters. In *European Conference on Computer Vision*, pages 857–871. Springer, 2012.

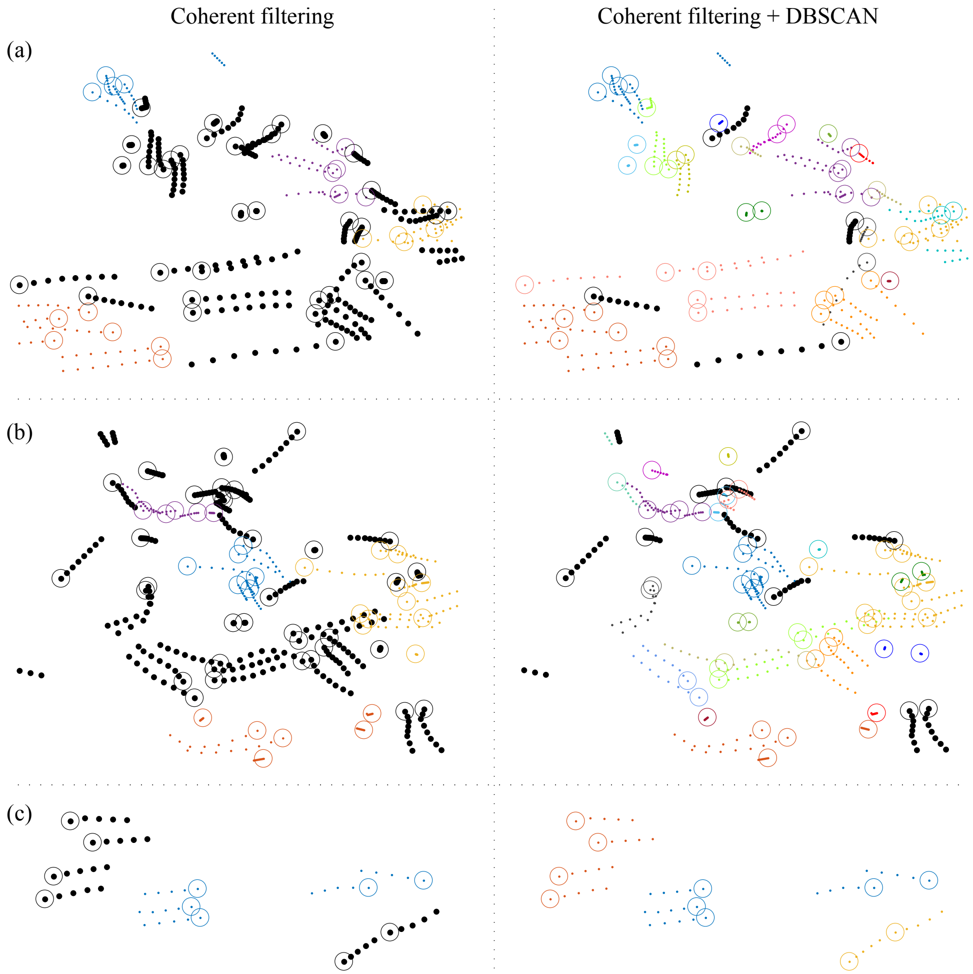

Figure 2: Representative examples for different coherent motion clustering methods. Same color denotes the same group. Black color denotes individual that has no coherence with others. Circles show the current position and dots show the trajectory history used for clustering. Best viewed in color.

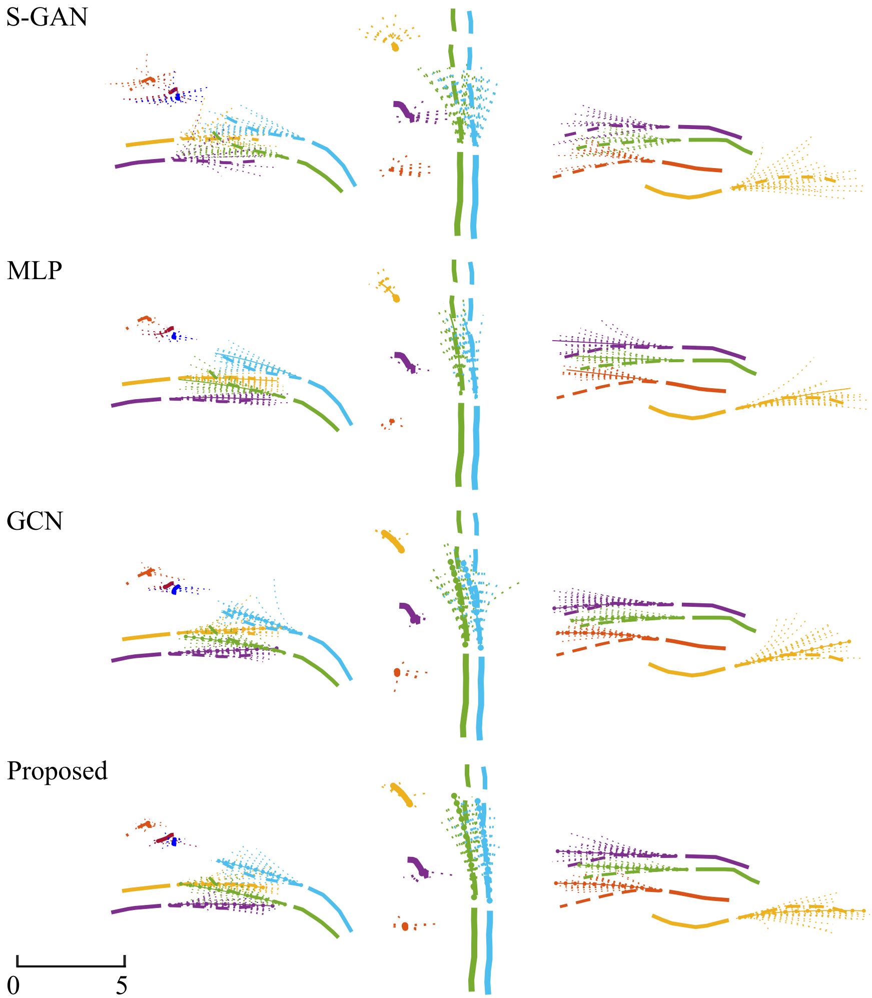

Figure 3: Examples for predicted trajectories visualization for different models. The observed trajectories are shown in solid lines, ground truth future trajectories are shown in wide dashed lines, generated 20 samples per model are shown in thin dashed lines. The dot-dashed lines denote the predictions of our VAE based model by applying the mean value (μ_z) of the distribution. Different humans are denoted by different colors.