SGCN: Sparse Graph Convolution Network for Pedestrian Trajectory Prediction

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A. Supplementary Material

To demonstrate the effectiveness and efficacy of our method, we provide this supplementary material which mainly contains the following contents: **1)** the visualization of *Motion Tendency*; **2)** the visualization of predicted trajectories in reality scenarios; **3)** a demonstration video, showing the effectiveness of our method by successive predictions; **4)** more visualization of our predicted trajectories. The code will be released upon paper acceptance.

A.1. Visualization of Motion Tendency

The Motion Tendencies are illustrated in Figure 1, in which the enclosed trajectory points in the same color make up a Motion Tendency. The Figure 1 shows scenarios with different numbers of pedestrians, including less crowded scenes and crowded scenes. For the Motion Tendencies, we find the moving direction of the last several trajectory points are more important than the first several trajectory points. By leveraging the Motion Tendencies, most of our predicted trajectories (in blue color) follow the moving direction of ground-truth trajectories (in red color). Specifically, in the scenario 4, the predicted trajectory on the upper left corner shows the larger deviation to the ground-truth than other predicted trajectories. We speculate the reason is that the Motion Tendencies in the ground-truth trajectory contains a hard turn-left, while the Motion Tendencies in the observation, marked in green color, do not contain it.

A.2. Predicted Trajectory Visualization

We showcase the trajectories predicted using the estimated bi-variate Gaussian distributions in two different scenarios. As shown in Figure 2, two pedestrians walk in parallel and gradually walk close to each other in the first scene (the first row). In the other scene (the second row), one pedestrian (green) meets two other pedestrians (yellow and blue) walking in parallel from the opposite direction. Our SGCN can predict trajectories with different patterns from the estimated distributions. In particular, the second column shows the best predicted results generated from the predicted bi-variate Gaussian distribution. In the third column, the moving directions of the generated trajectories have been adjusted to avoid possible collisions. As shown in the fourth column of Figure 2, another social attribute, *i.e.*, speed of pedestrians is changed, reflecting the pedestrians slowing down or speeding up to avoid crash. These cases show that the generated samples can reflect different expected social behaviors of pedestrians. Besides, in the bad cases (the last column), which show undesired behaviors such as collision and deflection.

Last but not the least, we compare the predictions of our SGCN against that of Social-GCNN [2] and SGAN [1]. The results are shown in Figure 3, in which the predictions of Social-GCNN and SGAN diverge and do not follow the pedestrian motion, while our SGCN is able to track and align well with the ground truth.

A.3. More Visualization

We present more visualizations of our predicted trajectories, as shown in Figure 4.

References

[1] Agrim Gupta, Justin Johnson, Li Fei-Fei, Silvio Savarese, and Alexandre Alahi. Social gan: Socially acceptable trajectories with generative adversarial networks. In *CVPR*, pages 2255–2264, 2018. 1

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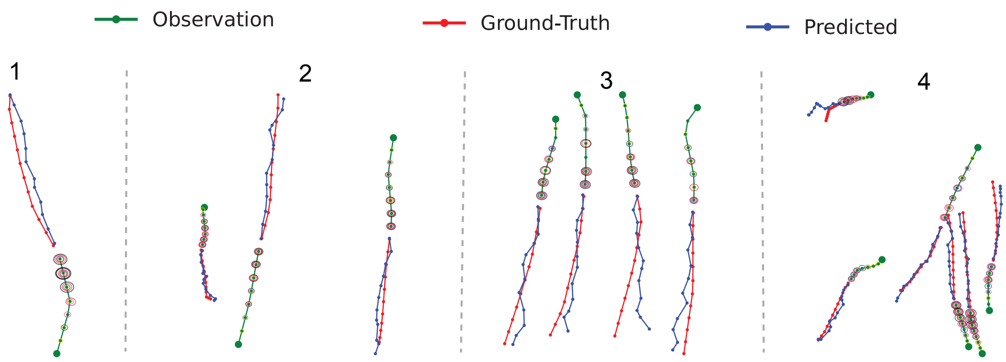

Figure 1. Visualization of Motion Tendency. The trajectory points marked by different color circles indicate different Motion Tendencies.

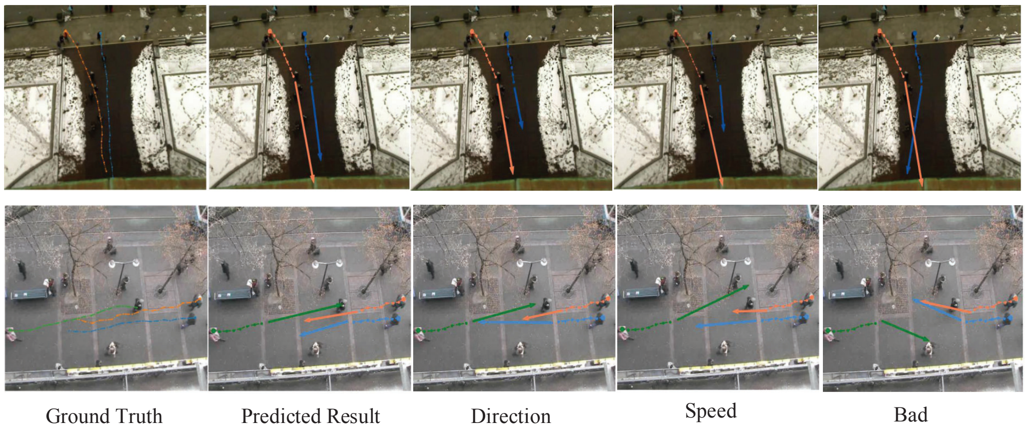

Figure 2. Trajectories generated by our SGCN in two different scenarios. The trajectories gradually turn into the same direction or point at opposite directions. In particular, the first column shows the ground truth, the second column represents the results predicted by our model, while the third and fourth columns show changes in direction or speed in the generated trajectories, and the last column shows few undesired behaviors.

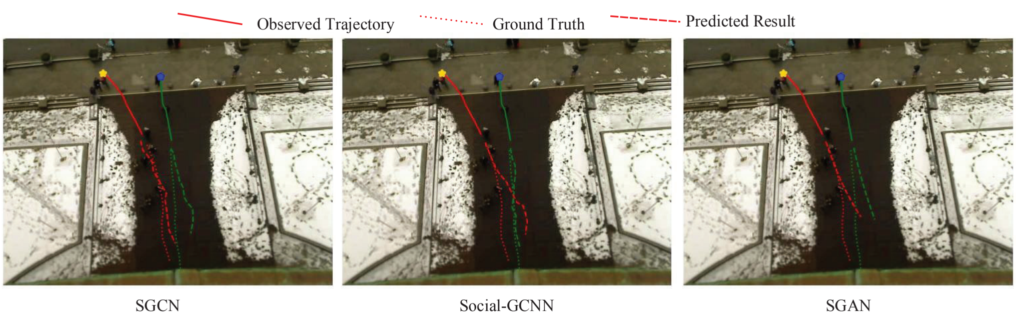

Figure 3. Comparison of averaged trajectories predictions with previous methods. The scenes are taken from the ETH [3] dataset.

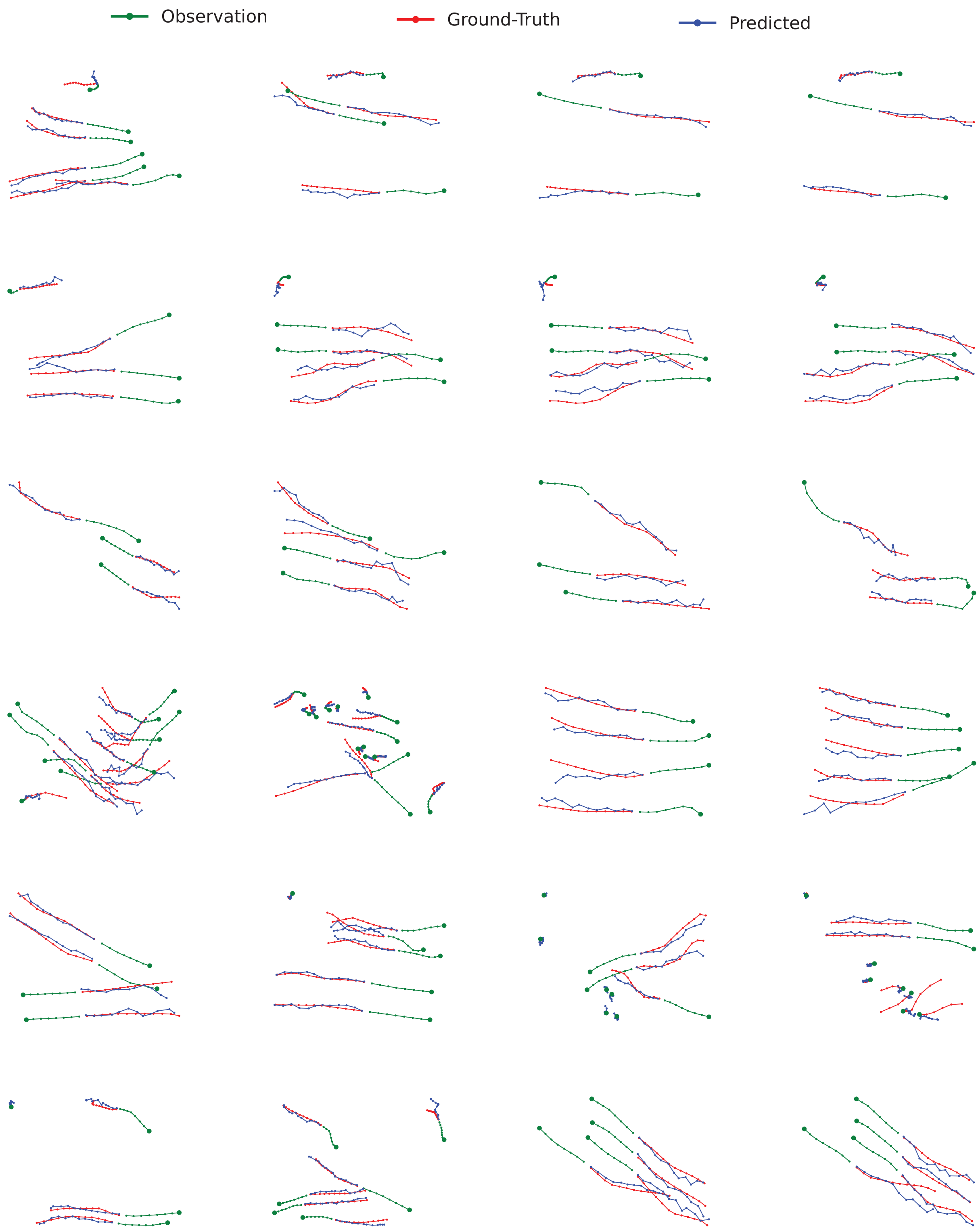

Figure 4. Visualization of more predicted trajectories from our SGCN.