RSG-Net: Towards Rich Semantic Relationship Prediction for Intelligent Vehicle in Complex Environments

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Abstract—Behavioral and semantic relationships play a vital role on intelligent self-driving vehicles and ADAS systems. Different from other research focused on trajectory, position, and bounding boxes, relationship data provides a human understandable description of the object’s behavior, and it could describe an object’s past and future status in an amazingly brief way. Therefore it is a fundamental method for tasks such as risk detection, environment understanding, and decision making. In this paper, we propose RSG-Net (Road Scene Graph Net): a graph convolutional network designed to predict potential semantic relationships from object proposals, and produces a graph-structured result, called “Road Scene Graph”. The experimental results indicate that this network, trained on Road Scene Graph dataset, could efficiently predict potential semantic relationships among objects around the ego-vehicle.

Index Terms—Relationship prediction, Environment understanding, Convolutional Graph Network

I. INTRODUCTION

Although autonomous driving systems have advanced significantly in recent years, one open problem is: how human drivers finish their task perfectly without high accuracy velocity/distance/position sensors? Although a human driver only provides very rough geometry result, it overwhelms autonomous driving systems on multiple tasks such as risk detection, scene understanding, vehicle behavior prediction, lane changing, etc. For example, most human drivers can predict a potential car accident in front of them and avoid it, while that is quite a hard task for AI.

An answer for this question is, human drivers can infer the relationship among surrounding objects with enormous accuracy. In contrast, so far the application of road semantic information is too simple to predict any semantic relationships. And in a complex environment like crossroads and parking lots, these relationships is even more important than the high-accuracy geometry, as these relationships indicate the previous and future status of objects. If such relationships could be captured by a model, the safety and comfort of autonomous system could be increased significantly. And, if failure happens, that information could be helpful for finding out its purpose.

In recent years, there is a great amount of research focusing on behavior detection and prediction. However, most of them are focused on trajectory prediction for pedestrians or vehicles. Only few research works mentioned such relational data. One reason for this is that trajectory prediction can directly increase the performance of self-driving tasks, while relational data, which are highly unstructured, are hard to process by state-of-art deep-learning models. Also, there are only a few datasets, like Honda Research Institute Driving Dataset (HDD)[1] and Road Scene Graph Dataset [2], which was based on nuScenes dataset [3], to include relational data.

In this paper, we propose RSG-Net (Road Scene Graph Net), graph convolutional network (GCN), designed to predict relationship information from surrounding objects’ proposals. Here, “objects” refer to three main categories: vehicle, pedestrian, and obstacle. This model takes those objects’ bird-view bounding box as input and proposes corresponding road scene graph, which is a topological graph in which nodes refer to objects and edges refer to the type of semantic relationship between objects. Fig. 1 illustrates a sample of rich semantic relationships provided by our model, and these relationships play a vital role in driver’s decision making. Furthermore, as many objects, like pedestrians or vehicles nearby, tend to move in the same mode, thus forming a group or cluster, their speed, direction, and behavior stay relatively the same. We brought in the “group” concept to keep the result simple, and user-friendly.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{Fig1.png}
\caption{Semantic relationships in an image recorded by vehicle recorder. Nodes in the right graph stand for the objects. And edges for pairwise relationships. Besides, we use the concept of “group” to describe multiple objects which have similar behavior.}
\end{figure}

In summary, our key contribution are as follows:

- We propose RSG-Net (Road Scene Graph Net) to predict potential semantic relationship from object proposals and outputs road scene graph for relationship prediction.
- Performance evaluations of RSG-Net using our Road Scene Graph Dataset[2].
- A benchmarking model of our Road Scene Graph Dataset to generate graphs from scratch.
This paper is structured as follows: Section II presents state-of-the-art works on drive scene understanding, relationship prediction and related datasets. Section III describes in detail our Road Scene Graph Net method, the model and evaluation metrics, while Section IV presents the results of different evaluation experiments. Finally, this paper is concluded in Section V.

II. RELATED WORK

A. Driving Scene Understanding: Tasks and methods

Significant progress has been made in many self-driving tasks like object detection, semantic segmentation and 3D pose estimation [4], [5], [6]. However, when it comes to semantic areas like behavioral prediction, relationship prediction, or potential risk evaluation, these approaches performance cannot catch up with human drivers yet. Recently, several papers have applied semantic information on intelligent vehicles, such as vehicle/pedestrian behavior prediction, trajectory prediction [7], potential risk detection. Besides that, researches are focusing on explaining the intention of human driver or self-driving system [8], [9], and then generate natural language description for it [10].

Since late 2020, some researchers are focusing on graph structure scene representation in the self-driving area. In [11], they proposed an interaction graph, which means two objects are connected if there might be an “interaction” between them. And it has been proved that this graph model, although quite simple, can increase the performance of driver behavior annotation. In [12], they generate another kind of graph representation, where edges stands for the relative motion between two objects. And in [13], the graph is more than a plural graph which connects object with lanes. In our own previous work [2], we proposed road scene graph concept, and proposed a model that takes this graph as input and predict the graph in the next few seconds.

Undoubtedly, a general problem of these task-specific semantic researches is that datasets are insufficient. Some data like driving behavior, risky scene, and even car accidents, are extremely hard to obtain. Luckily, in 2019 and 2020, an increasing amount of high-quality semantic driving dataset appeared. Some of them are common datasets, like nuScenes [3], semantic KITTI [14] and Waymo [15]. And others, although with less amount of data, are task-specific datasets, e.g. Road Hazard Stimuli dataset [16] for road hazard and risk annotation, Honda HDD dataset [1] for behavior prediction, and our Road Scene Graph Dataset [2]. Besides that, driving simulators like CARLA [17] and Airsim [18] are even more important over time as for scene replay, data augmentation and reinforcement learning [19].

B. Relationship Prediction and Scene Graph Generation

With the fast development of computer vision techniques, scene understanding –other than object detection– has been the new frontier of computer vision. And it has been proved that such scene understanding tasks could also improve the performance of fundamental tasks like object detection[20]. From input/output aspect, scene understanding includes multiple tasks like image captioning, visual question answering (VQA)[21], [22] and scene graph generation [11], [12], [13], [23], [24], [25]. In this paper, we are focusing on scene graph generation tasks.

From the category aspect, there are common scene graph generation (relationship prediction) tasks and task-specific scene graph generation. Both of them benefit from the theoretical breakthrough of graph neural network and graph generation network[26], [27], [28], [29]. In the common area, their models were trained by large open image datasets, such as Imagenet and MS COCO. Also, there are some dataset designed for this task, like Visual Genome [30] and VRR-VG [31]. However, for the task-specific aspect, such as road scene graph generation for intelligent vehicles, there are only several datasets and methods [11], [12], [13] that can fit the need.

III. METHODS

A. Dataset setup

Research in this paper an incremental work where we further exploit the potential of our dataset Road Scene Graph Dataset[2]. Road Scene Graph Dataset includes 500 scenes, each one is around 20 seconds and sampled at 2 Hz. so there are around 20,000 scene graphs in this dataset. The categories of objects and relationships are listed in table I. Here, “objects” indicate the high-level categories of objects, e.g. “Human” includes pedestrians and workers, “Obstacle” includes traffic cones, debris, barriers, etc. For relationship data, we selected 21 kinds of common and basic relationships.

| Objects and Relationships in Road Scene Graph Dataset |
|------------------------------------------|
| Human | Vehicle | Obstacle | Traffic-sign |
|------|---------|----------|-------------|
| Human | Group   | Behind   | Obstruct   |
|       |         | on-lane  | waiting-ts |
| Vehicle (cyclist) | Group | Same-lane | same-lane  |
|       |         | waiting-ts | overtaking |
| Obstacle | -      | -        | Group      |
| Traffic-sign | -     | -        | behind     |

B. Road Scene graph Generation with Message Passing Network

Road Scene Graph (RSG), which is a structured data representation of objects and their semantic relationships around the ego vehicle, can be defined as a tuple $G = \langle V, E \rangle$.

- $V = \{v_1, v_2, \ldots, v_n\}$ stands for the object status. The nodes in $V$ are manually defined: $v_i = \langle i_{nt}, x_i, y_i, v_{x_i}, v_{y_i}, a_{x_i}, a_{y_i}, y, p, r \rangle$, where $i_{nt}$ represents the one-hot label of node’s type, position $(x_i, y_i)$,
velocity \((v_x, v_y)\), acceleration \((a_x, a_y)\), and heading angles \((\text{yaw}, \text{pitch}, \text{roll})\). In nuScenes dataset, we ignore the first and final frames as their object status are incomplete.

- \(E = \{e_{ij} \mid v_i, v_j \in E\}\) is the relationship set of the graph \(G\). For the input graph \(E_{in}\), the elements are \(e_{i \rightarrow j} = (dx, dy, dxv, dyv, P(R|v_i, v_j))\), \(dx, dy, dxv, dyv\) correspond to the position and velocity difference between two objects. For generated graph \(E_{gen}\), the elements \(e_{i \rightarrow j} \in E_{gen}\) are the one-hot prediction vector indicates the predicted relationship.

For \(P(r_i \mid v_i, v_j)\), where \(r_i \in R\), and \(R\) is for the relationship set, it is well-known that the statistical information of object co-occurrence is a strong prior knowledge. So, inspired by [32], we count the relationship occurrence in Road Scene Graph dataset as prior knowledge. For example, if \(r_i\) means “passing-by” relationship and \(v_i, v_j\) is for a human and a vehicle, then \(P\) stand for the statistical co-occurrence of a vehicle passing by a pedestrian. In this way, we not only increase the performance but also significantly restrain the occurrence of incorrect relationships like “\(<\text{barrier} – \text{passingby} – \text{another barrier}\>\).”

And for the graph generation network, our model was inspired by the graph gated network structure, a popular structure in multiple graph generation networks, to propagate node messages in graph [25], [28], [32], [33].

Different from common scene graph generation problems, in this task we do not need to simultaneously predict object status and their relationships, as their bounding boxes could be obtained from perception module in a self-driving system, with LiDAR auxiliary bounding box regression, it would be very accurate. So, we focus instead on the edge prediction part. However, predicting edge is much more difficult than predicting node status, because compared to update only node status, update node and edge at the same time will bring additional complexity to the model and training process. [25] proposed an interesting insight that, if we take relationship as an individual node, then road scene graph will turn to a bipartite graph. In other words, node vector \(V \in G\) could be separated into 2 sets: object set and relationship node set. So here we turn the original graph into its dual graph. And edge type prediction problem will be turned into a node prediction problem, which is much easier to solve. In [25], the scene graph generation problem could be formulated as finding the optimal \(x^* = \arg \max_x P(r(x|I, B))\) given the image \(I\) and bounding box proposals \(B\). Therefore, \(P(r(x|I, B))\) can be defined as follows:

\[
Pr(x|I, B) = \prod_{i \in V} \prod_{j \notin i} Pr(x_i^{cls}, x_i^{bbox}, x_i \rightarrow j|I, B) \tag{1}
\]

In this paper, as we do not need bounding box detection. In contrast, we utilize the relationship prior distribution to improve accuracy. The road scene graph generation problem is:

\[
Pr(E_{gen}|V_t, P(r_i \mid v_i, v_j)) = \prod_{i \in V} \prod_{j \notin i} Pr(e_{i \rightarrow j}|V_t, P(r_i \mid v_i, v_j)) \tag{2}
\]

Eq. 3 lists the update step formula for our GRU model:

\[
\begin{align*}
r_t &= \sigma(W_{xr}f_t + W_{hr}h_{t-1}) \\
z_t &= \sigma(W_{xz}f_t + W_{hz}h_{t-1}) \\
h_t &= \operatorname{tanh}(W_{xh}f_t + W_{hh}r_t \odot h_{t-1}) \\
\hat{h}_t &= (z_t \odot \tilde{h}_{t-1}) + (1 - z_t) \odot \bar{h}_t \\
a_t &= \sigma(W_hr + h_t)
\end{align*}
\]

Here, \(\sigma()\) is for sigmoid function, and all \(W\) is for learnable parameters. \(\tilde{h}_t\) are used as previous hidden state. Update gate \(z_t\) has a role to adjust the previous information \(\tilde{h}_{t-1}\). Finally, binary output \(a_t\) is obtained after a fully connected layer \(W_{r}, h_t\).

C. Metrics

Another fundamental difference between common scene graph prediction tasks and Road Scene Graph prediction is the time subjectivity. In other words, the starting time and ending time of a specific relationship may vary by different annotators. For example, as Fig. 3 illustrates, when a vehicle passing by the pedestrian, starting and ending time among different annotator’s annotations will vary. In common scene graph prediction tasks, this problem does not exist as it takes a single image, not a sequence of images as input. As a supplementary experiment, we invited 6 annotators, to label 10 relationships in 10 different scenes. The results show that the time gap will be about 3 to 7 frames (1.5 to 3.5 seconds) on average. To reduce the impact it makes into the model performance, we bring out the slope weight function. As Fig. 4 illustrates, it brings a little bit relaxation at the start and end time of relationships. Eq. 4 lists the slope weight function when ground truth is \(\frac{b-a}{2}, \frac{d-c}{2}\). When calculating the loss function using sparse softmax cross entropy, we multiply
this weight as a penalty item to every edge prediction. So the relationships at the “slope”, whether successfully predicted or not, will influence the model less than normal relationships.

\[
w = \frac{2}{d + c - a - b} - \frac{1}{b - a} \quad \text{if } x \in [a, b]
\]

\[
w = 1 \quad \text{if } x \in [b, c]
\]

\[
w = \frac{2}{d + c - a - b} + \frac{1}{d - c} \quad \text{if } x \in [c, d]
\]

Fig. 2. Representation of our graph prediction model. It takes object proposal as input and firstly generates a dense graph and its dual graph from these proposals. Then, we use a edge message pooling model and edge GRU to propagate messages through edges. Here we stacked the model 4 times. ⊕ symbol in edge message pooling model stands for a learnable parameter set. This model is inspired by [25], which is an effective graph generation framework for common relationship prediction.

Fig. 3. A brief example of annotation subjectivity in Road Scene Graph Dataset. Here the horizontal axis stands for the time (frames). While a car passing by a pedestrian, different annotators will propose slightly different annotations.

We evaluate our method for generating scene graphs in two metrics: R@K metric[35] and Pairwise prediction accuracy. R@K metric is used to evaluate the difference of a generated graph to the ground truth, while pairwise prediction accuracy is used to evaluate the prediction accuracy for a specific kind of relationship, like “waiting-for” or “passing-by”. Compared with normal metrics like mAP, R@K metric is significantly better. As in most of the time the scene graph is a sparse graph, more than 95% percent of relationships are actually “No relation”. Metrics like mAP would falsely penalize positive predictions on unlabeled relationships, and suppress the form of relationship.

IV. EXPERIMENT

Similar to our prior work [2], we generated Road Scene Graph dataset for training and evaluation, this dataset has been introduced in Section III-A. Fig. 4 illustrates the user interface of our data annotator. We set the final 10% scenes in dataset as test set, and use the remaining for training set.

Fig. 4. Road Scene Graph annotator we used to set up experiment dataset. This annotator was created to enable annotating relationships and group information in nuScenes dataset.

Fig. 5 illustrates a sample frame in nuScenes, and its corresponding road scene graph (scene number 0103, frame 21/39). Here, the ego vehicle is following the vehicle in front of it, and the vehicle on the opposite lane is waiting for pedestrian crossing the road while trying to turn right. Vehicles on the left branch are also waiting for the pedestrians. By arranging all objects into a graph, we can visualize a very complex traffic scene and objects’ interaction. Also, this graph data representation could be easily processed by graph neural networks.

Compared with our previous methods [2], our current model performs significantly better on R@K recall and Pairwise accuracy. Table II lists the R@K metric and Pairwise accuracy performance of our model. Here the NGPGV (Next
In this paper, we proposed RSG-Net, a graph convolutional network to model fundamental semantic relationships between vehicles, pedestrians, and other objects, and arrange them into a graph structure. Experiments conducted on Road Scene Graph Dataset indicate that our model could capture and predict semantic relational data. In future works, this road scene graph could be helpful for multiple tasks like potential risk detection, road scene captioning, etc. Besides that, the performance of our current model could be further optimized with the rapid theoretical breakthrough of graph networks.

V. CONCLUSIONS

In this paper, we proposed RSG-Net, a graph convolutional network to model fundamental semantic relationships between vehicles, pedestrians, and other objects, and arrange them into a graph structure. Experiments conducted on Road Scene Graph Dataset indicate that our model could capture and predict semantic relational data. In future works, this road scene graph could be helpful for multiple tasks like potential risk detection, road scene captioning, etc. Besides that, the performance of our current model could be further optimized with the rapid theoretical breakthrough of graph networks.

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