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ROAD TRAFFIC PREDICTION USING TMS-GCN BASED ON REGION LEVEL TRAFFIC INFORMATION PREDICTION

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ABSTRACT

Region-level traffic information can characterize dynamic changes of urban traffic at the macro level. Real-time region-level traffic prediction help city traffic managers with traffic demand analysis, traffic congestion control, and other activities, and it has become a research hotspot. In this project, we utilize a large-scale GPS data set, a framework for evaluating and discovering data-driven region-level-based traffic prediction. However, due to dynamism and randomness of urban traffic and the complexity of urban road networks, the study of such issues faces many challenges. This work proposes a new deep learning model named TmS-GCN to predict region-level traffic information, which is composed of Graph Convolutional Network (GCN) and Gated Recurrent Unit (GRU). The GCN part captures spatial dependence among regions, while the GRU part captures the dynamic change of traffic within the region. Model verification and comparison are carried out using real taxi GPS dataset. Experimental results demonstrate the feasibility and effectiveness.

Keywords: Traffic Prediction, TMS-GCN, Region-Level Traffic Prediction, Traffic Information Prediction, Road Traffic Prediction.

I. INTRODUCTION

Traffic prediction is the task of forecasting real-time traffic information based on floating car data and historical traffic data, such as traffic flow, average traffic speed and traffic incidents. Overview of the traffic prediction includes i)Traffic status prediction: It is popular to use the navigation system of the electronic map to avoid congested roads when we plan to leave one place for another. The key ability to achieve the target is to predict which roads will be congested in the future time. In other words, we need to predict the traffic status for each road. However, it is typical to measure traffic status with average traffic speed or travel time. The slower the traffic speed or the more the travel time, the worse the traffic status. Therefore, the traffic status prediction can be regarded as the traffic speed or travel time prediction, which are regression problems. Moreover, we can measure the traffic status with different types (e.g., smooth, light congestion and heavy congestion) by splitting the traffic speed into different continuous intervals, where predicting the traffic status becomes a classification problem. ii)Traffic flow prediction: Recently, there exist some stomp events caused by excessive traffic. The main reason is that the government cannot monitor and guide the flow of people in time. Hence, it is significant to predict traffic flows in future time. Moreover, traffic flow can be divided into two types: network-based and region-based. The first type infers the number of vehicles collected by loop detector sensors, which are installed on both endpoints of the roads. As for the second type, we split the whole city into different regions and regard the number of crowds leaving one region for another as the region-based traffic flow. Therefore, the region-based traffic flow can be further divided into in-flow and out-flow. For example, if there are 100 people leaving the region A for the region B, both A's out-flow and B's in-flow would increase 100. iii)Traffic flow prediction: Recently, there exist some stomp events caused by excessive traffic. The main reason is that the government cannot monitor and guide the flow of people in time. Hence, it is significant to predict traffic flows in future time. Moreover, traffic flow can be divided into two types: network-based and region-based. The first type infers the number of vehicles collected by loop detector sensors, which are installed on both endpoints of the roads. As for the second type, we split the whole city into different regions and regard the number of crowds leaving one region for another as the region-based traffic flow. Therefore, the region-based traffic flow can be further divided into in-flow and out-flow. For example, if there are 100 people leaving the region A for the region B, both A's out-flow and B's in-flow would increase 100. iv)Travel demand

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prediction: Transportation companies provide online taxi service for users. They need to predict people's travel demands in order to better dispatch vehicles for different regions. For example, they should dispatch more vehicles to residential areas during the morning rush hour. In contrast, they should dispatch more vehicles to office zones during the evening rush hour. Generally, predicting travel demands is based on regions, so we also call it region-based travel demand prediction.

Vehicles equipped with GPS devices that travel on urban roads can dynamically upload their latitude, longitude, velocity, and other data to a server. When the number of such vehicles reaches tens of thousands, traffic managers can obtain dynamic traffic information of urban roads, such as traffic flow and traffic speed, to support various research and applications in the field of Intelligent Transportation System. For instance, identifying areas of interest (AOIs) based on taxi GPS in New York City [1], estimating urban network-wide traffic speed estimation based on massive ride-sourcing GPS traces [2], assessing individual activity-related exposures to traffic congestion using GPS trajectory data [3], and so on. Therefore, using GPS data to perform region-level traffic prediction is reasonable and representative. Region-level traffic prediction, on the one hand, can support the development of real-time traffic management applications such as traffic control and traffic guidance, and, on the other hand, it can also help carry out real-time OD estimation [4]. For instance, using the average speed of a specific region deviates from the average value, and the traffic manager can reschedule the traffic signal in advance or send the police to divert traffic. With region-level dynamic traffic flow information, which represents travel demand, companies can dispatch vehicles based on this forecast information to obtain greater economic benefits. However, due to the complexity and relevance of the traffic state in both the time and space dimensions, traffic prediction at the region level is of a great challenge. Firstly, traffic prediction is a time-series task that uses historical traffic information in the region to forecast future traffic information. As a result, many studies based on time series models, such as the Autoregressive Integrated Moving Average (ARRIMA) model [5], the Kalman filtering model [6], Bayesian network [7], Neural Network [8], Recurrent Neural Network [9], and so on, have been proposed. However, these models only consider temporal dependence and ignore spatial dependence of adjacent regions, which has an impact on prediction result. In recent years, some studies have proposed new hybrid models based on the time-series model and spatial feature mining model to comprehensively use the temporal dependence of the predicted region and spatial dependence from adjacent regions to forecast traffic information [10,11].

II. METHODOLOGY

SPATIAL AND TEMPORAL FEATURE EXTRACTION

Firstly, the urban area is divided into regions, a region graph is conducted, and traffic information (i.e., traffic speed, traffic demand, etc.) in each region is obtained. Secondly, the graph convolutional neural network is used to capture the spatial features. Finally, the outputs of the GCN part are input into the GRU part to forecast future traffic information. We proposed a complete region-level traffic prediction method named TmS-GCN composed of GCN and GRU. Based on GCN, TmS-GCN can capture multi-spatial correlation features of regions on non-Euclidean distance data composed of divided regions. In addition, based on GRU, TmS-GCN can capture temporal features of traffic parameters within the region.

TMS-GCN BASED REGION LEVEL TRAFFIC INFORMATION PREDICTION

Graph convolution network extracts the spatial characteristics by defining the road network graph. Benefited from different kinds of the road network graph, the non-European spatial features of the road network from different angles are extracted by the graph convolution network. Consequently, the method of definition of the road network graph is absolutely critical. With the accurate coding in aspect of the spatial correlation among all roads in the road network graph, the graph convolution network has stronger learning ability and more accurate prediction effect.

The road network graph is represented as an undirected graph $G = (V, E, W)$ where each node $v_i (v_{ij} \epsilon V)$ represents the road in the road network, the number of all roads is represented as $|V| = N$, each edge $e_{ij} (e_{ij} \epsilon E)$ represents the correlation between road v_i and v_j. The edge weight $w_{ij} (w_{ij} \epsilon W)$ of edge e_{ij} represents correlation coefficient between road v_i and v_j. The larger the edge weights are, the stronger the correlation among roads become in a certain aspect. The four types of road network graph are constructed in this paper.

Namely, the road topological graph G_r the road weighted topological graph G_w, the traffic historical pattern graph G_p and the road attribute similarity graph G_s.

1) Road Topological Graph: The road topological graph is expressed as an undirected graph $G_r = (V, E, W)$, where the weight $w_r(i, j)$ of the edge e_{ij} is the reciprocal of the number of edges traversed by the shortest path from road v_i to road v_j in the road network. Therefore, with the distance among the roads becoming shorter, the corresponding weight in the topological adjacency matrix becomes larger. Then, the adjacency matrix W_r of road topological graph G_r is expressed.

2) Weighted Topological Graph: The road topological graph defines the topological relationship of roads merely, however, the impact on spatial correlation of the length of roads is important as well. Like the road topological graph, the road weighted topological graph $G_w = (V, E, W_s)$ is defined in this paper. The weight $w_w(i, j)$ of edge e_{ij} is expressed, where $\mathrm{length}(v_m)$ represents the length of all roads in the shortest path from the road v_i to road v_j in the road network. Then, the adjacency matrix W_w of weighted topological graph G_w is expressed.

$$\omega_w(i, j) = \frac{length(v_i) + length(v_j)}{length(v_m)}$$

Spatiotemporal Feature Extraction Layer: The spatiotemporal feature extraction layer is composed of a spatial feature extraction layer and a temporal feature extraction layer. First, the multi-channel traffic data are inputted into the spatial feature extraction layer to extract different aspects of spatial features. The spatial feature extraction layer is composed of two layers of multi-graph convolution and fusion operations to complete the extraction of the full-map road spatial features and fuse with multi-channel features; secondly, the spatial features extracted at each angle are inputted to the temporal feature extraction layer. The extraction layer consists of a conventional self-attention mechanism, and it can effectively capture the temporal correlation between different historical data. Finally, the spatiotemporal features under the channels based on different graph types are used as the output of the spatiotemporal feature extraction layer.

1) Graph Convolution for Traffic: The traffic network usually presents the structural form of graph with non-Euclidean properties. Aiming to not only more in line with the actual road distribution, but also more conductive to model learning the spatial features of the road, the road network is represented as the mathematical method of graph.

2) Graph Convolution Network: Although each layer of graph convolution only considers the direct neighborhood in graph, the grid depth is reduced by stacking multi-layer local map convolution layers, so as to simplify the model and build a deeper architecture to expand the receptive field.

3) Multi-Dimensional and Multi-graph Graph Convolution: Considering the diversity of the input traffic condition data, the traffic prediction task based on one kind of data alone is not comprehensive. In order to predict the traffic condition by making full use of the existing data, and consider the impact of various traffic data on the prediction accuracy, the variety of feature embedding are extracted. Moreover, considering the certain correlation among the different types of traffic data, the public information of heterogeneous traffic data is extracted by shared multi-channel parameter graph convolution model. The multi-channel and multi-graph graph convolution proposed of two parts, namely the angle of multi-channel and multi-graph. For the multi-channel's point of view, the double-layer graph convolution with shared multi-channel parameter is designed, so that the multi-channel input data can be operated by graph convolution model, and the model also extracts the shared features from the different type of input data. In this paper, the multi-channel inputs are average speed and average flow of roads separately. For the angle of multi-graph of graph convolution, namely the four graphs defined, the graph convolution is operated based on every graph data, so that the spatial correlation features of traffic data are extracted in different angles. The graph convolution of input data from different channels is calculated in parallel, then the feature of fusion is calculated by the fusion layer, so that the merged feature embedding is obtained as the output of the graph convolution of the double-layer and two-channel under a certain graph.

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DISTANCE EVALUATION

1. Road distances among different routes are composed in detail.
2. Using standard shortest path finding algorithms (Dijkstra algorithm) are applied to optimize/minimize these distances for both single-source and all-pairs shortest path problems.

The euclidean distance is the distance between two points in euclidean space. The two points P and Q in two dimensional euclidean spaces and P with the coordinates (p1, p2), Q with the coordinates (q1, q2). The line segment with the endpoints of P and Q will form the hypotenuse of a right angled triangle. The distance between two points p and q is defined as the square root of the sum of the squares of the differences between the corresponding coordinates of the points. The two-dimensional euclidean geometry, the euclidean distance between two points a = (ax, ay) and b = (bx, by) is defined as:

$$d(a,b) = \sqrt{(bx - ax)^2 + (by - ay)^2} \qquad \text{Equation (13)}$$

Euclidean distance algorithm computes the minimum distance between a column vector x and a collection of column vectors in the code book matrix cb. The algorithm computes the minimum distance to x and finds the column vector in cb that is closest to x. Figure shows Euclidean distance algorithm.

$$d(a,b) = |p - q| \qquad \text{Equation (14)}$$

$$\sqrt{(p1 - q1)^2 + (p2 - q2)^2 + \cdots + (pn - qn)^2}$$

$$= \sqrt{\textstyle\sum_{i=1}^{n}(pi - qi)^2} \qquad \text{Equation (15)}$$

In one dimension, the distance between two points, x1 and x2, on a line is simply the absolute value of the difference between the two points as:

$$= \sqrt{(X2 - X1)^2} = |X2 - X1| \qquad \text{Equation (16)}$$

In two dimensions, the distance between P = (p1, p2) and q = (q1, q2) as:

$$= \sqrt{(p1 - q1)^2 + (p2 - q2)^2} \qquad \text{Equation (17)}$$

Step1: load the column vector x;

Step2: load the code book;

Step3: minimum distance is initially set to the first element of cb.

Step4: i.e. set idx=1;

Step5: compute distance by normalized values of (x-cb) for all cb;

Step6: if d is less than distance set distance is equal to d;

Step7: set idx=index;

Step8: end

III. MODELING AND ANALYSIS

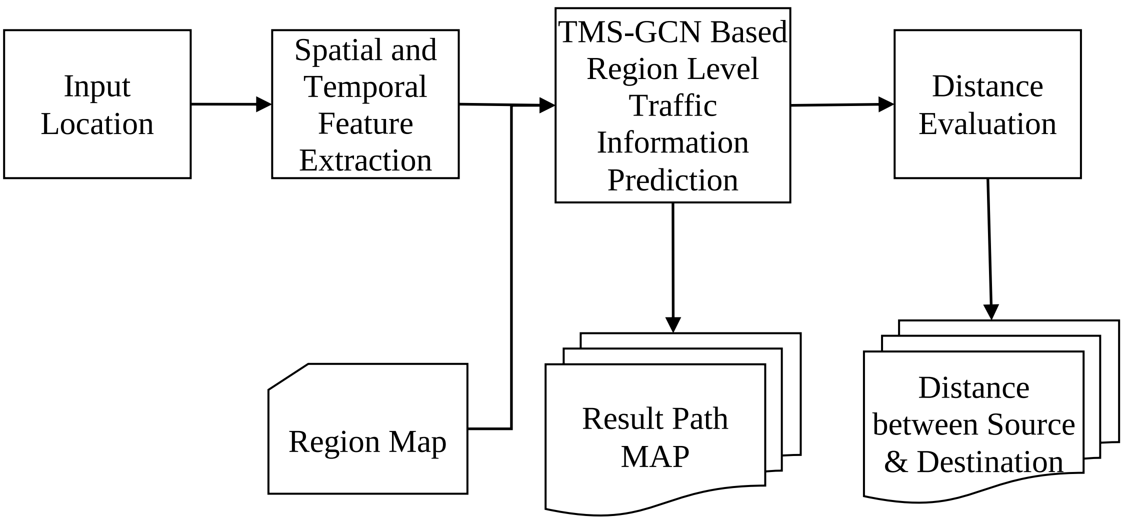

Figure 1: Architecture of the proposed model

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Figure 1 shows the completed architecture of our proposed method.

IV. RESULTS AND DISCUSSION

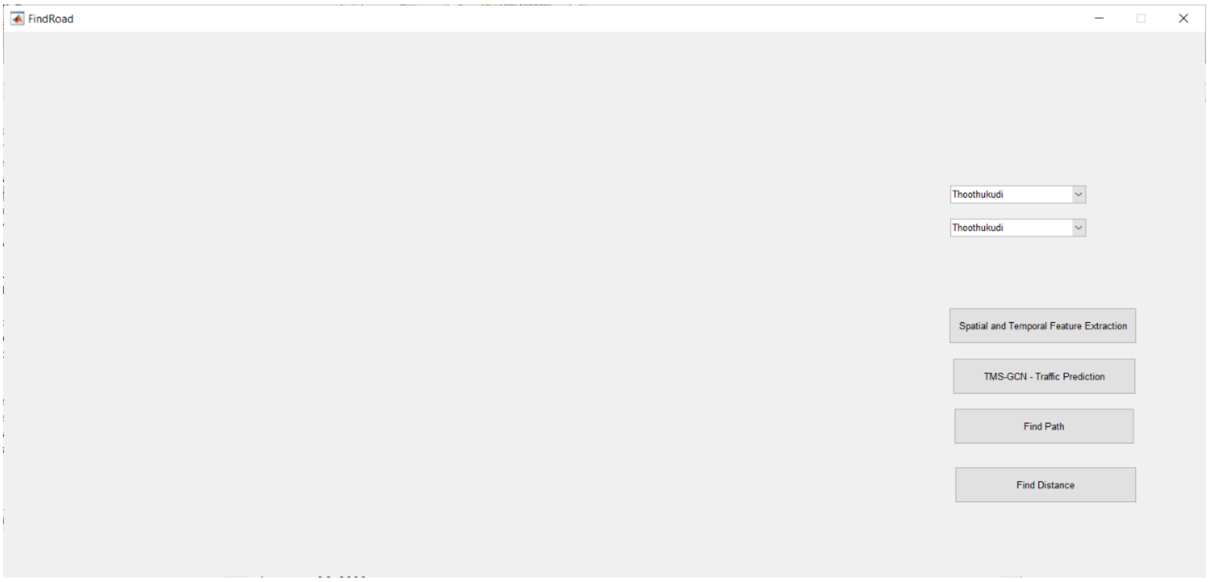


Figure 2: UI design of the proposed system

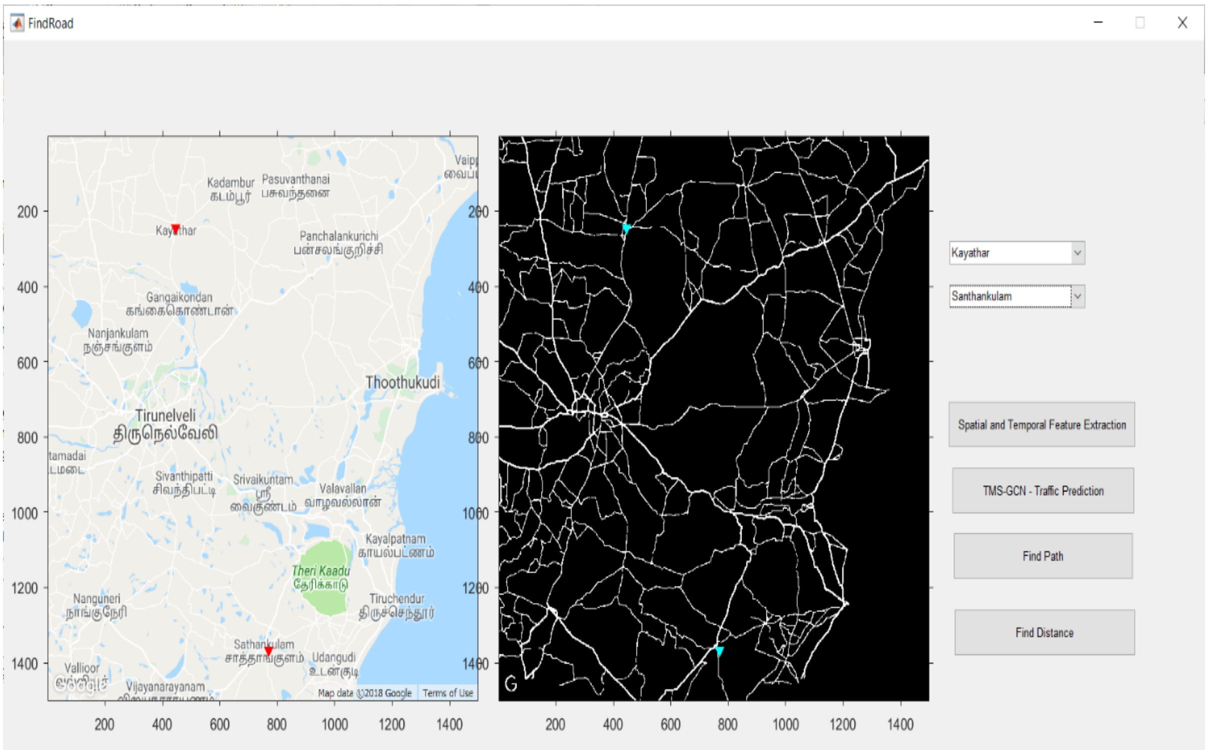
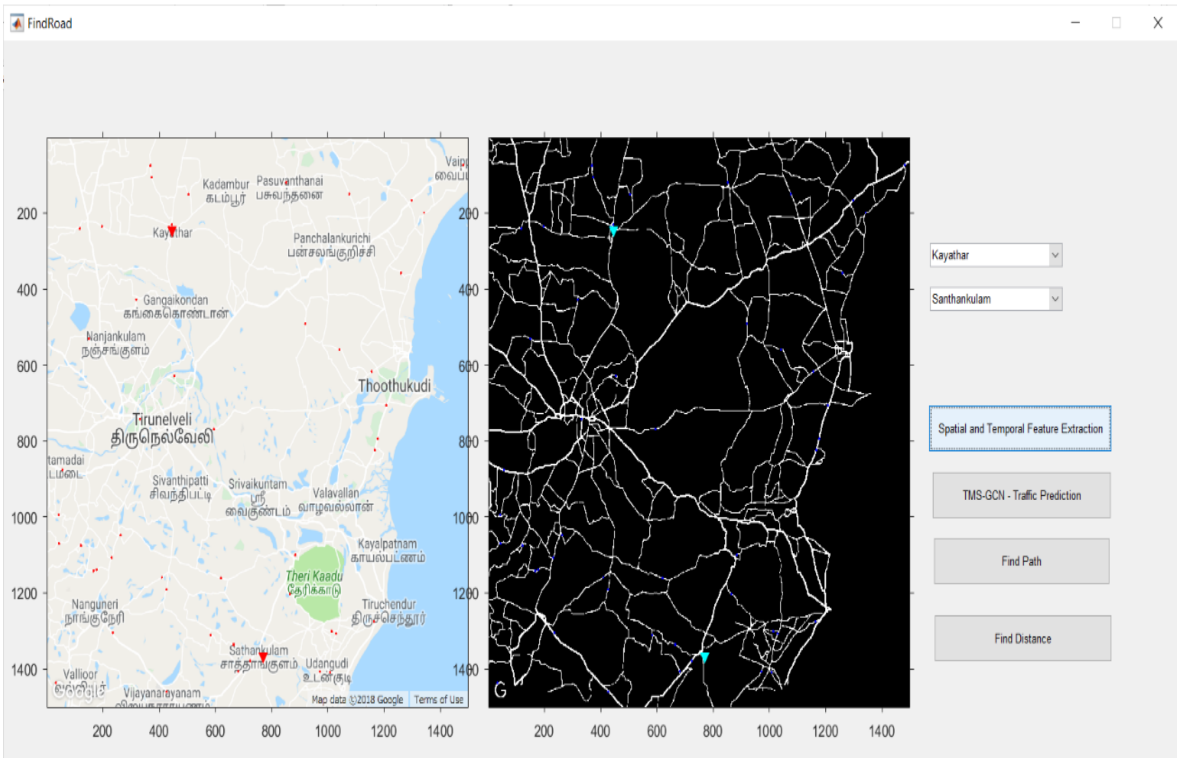
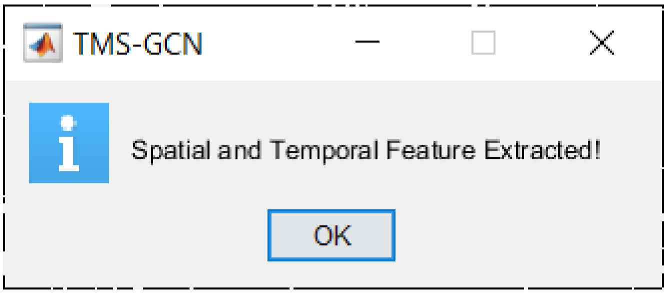


Figure 3: Selected source and destination from the map



4 a)



4 b)

Figure 4(a), (b): Extracted spatial and temporal features

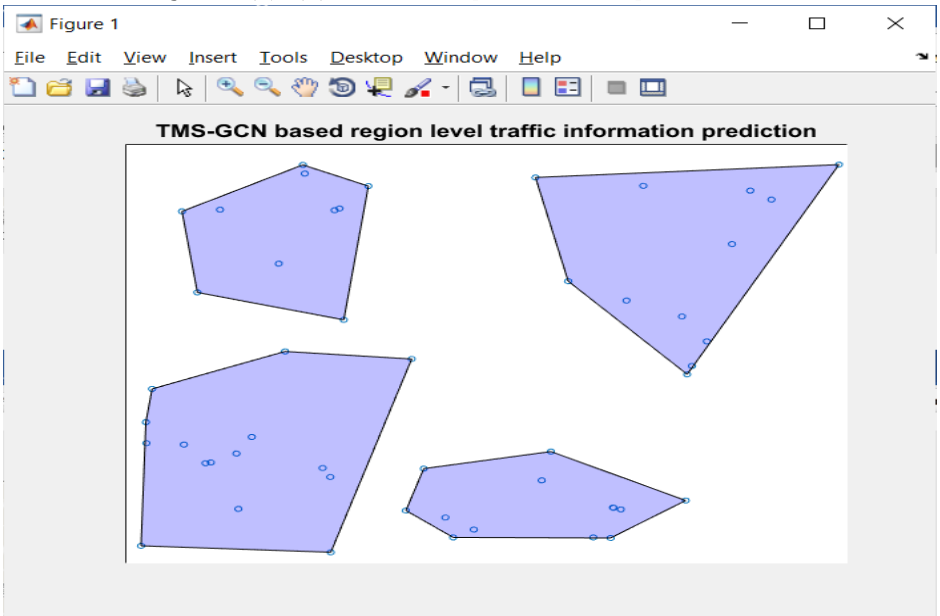


Figure 5: TMS-GCN based region level traffic prediction

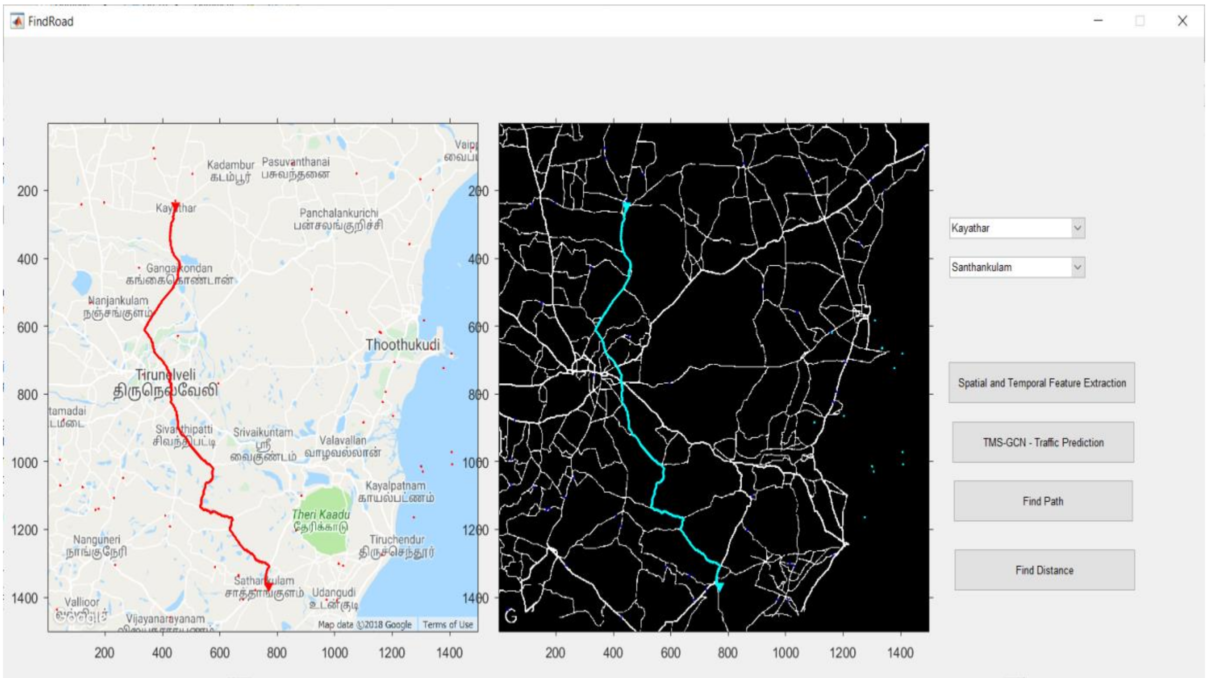


Figure 6: Predicted route map

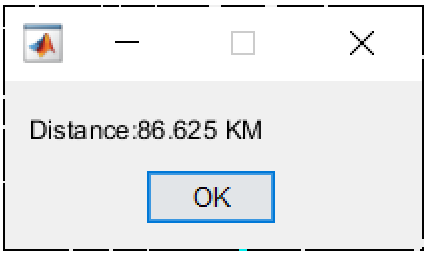


Figure 7: Predicted distance

Figure 2 shows the UI design of the proposed system. Figure 3 shows the selected source and destination from the map. Figure 4(a), (b) shows the extracted spatial and temporal features. Figure 5 shows the TMS-GCN based region level traffic prediction. Figure 6 shows the predicted route map. Figure 7 shows the predicted distance.

V. CONCLUSION

The proposed methodology was tested over several road maps of India. Simulation results clearly indicate drastic reduction in travel time, compared to path finding methods using conventional techniques. Implementing the proposed system in Navigation systems could help to reduce economic and environmental losses caused due to congestion. Also since the system is based on real-time traffic and dynamically predicts routes as driver's progress towards their destination, there is minimal chance that people starting from the source to the same destination would ever cause congestion for other drivers

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