PREDICTION OF TRAVEL TIME FOR LARGE SPATIAL GRAPH

Abhijeet Waghmare[1], Prof.D.D. Gatade[2]
Department Of Computer Engineering, SCOE PUNE,
Savitribai Phule Pune University, Maharashtra, India

Abstract

The survey of traffic condition between roads of urban network, is very useful to estimate travel time and to improve effectiveness of Intelligent Transportation Systems. This paper gives an approach depending on graph-theory for spatial dependence between roads of the same network. Representing the road network as a graph, the local neighbours of each road are obtained utilizing a lower complexity variation of Modified Graph Traversal algorithm. A linear dependency based metric is applied on the chosen graph nodes for an endorsed number of level sets of neighbours.

In order to evaluate the effect of the new strategy to the traffic prediction, the most correlated roads are utilized to manufacture a Traffic Prediction Model, taking the possible time delays of traffic between the interrelated roads. This system use modified transversal algorithm and Traffic Prediction Model to improve the accuracy of getting shortest path time from source to destination location.

Index Terms: data processing, Graph theory, Time series anal-ysis, Travels time prediction.

I. INTRODUCTION

The term graph is the backbone of the computer network. The graph is used for a different domain. The graph gives the visualization of any network. It is used for social network, road network, railway network and internet traffic network. The graph is static and dynamic. It changes with respect network topology and datasets. The edge of the graph is called link it represent the relation between nodes of the graph. The link is also dynamic and it has certain weight. It is used for transfer data. Graphs serve as a mathematical model for network modeling and are used in many fields. As Easley and Kleinberg[1] pointed out, graphs can be used in order to model networks from several different fields such as: (i) communication networks, where nodes represent computers and edges direct links, through which messages can be transmitted, (ii) social networks, where nodes represent people and edge social interactions between them, and so on. Among other application domains, graph theory is used in transportation as well, where according to a graph is called transportation network when it is used to model the transportation of a commodity from one place to another. According to there are mainly two graph representations of an urban structure: the primary and the dual.

The former is based on the relations between junctions through their streets, where every node represents a junction and every edge a street or route between junctions. The latter describes the relationships between the roads of the network, in which every node represents a street and every edge a common point between any two streets. Both representations are used for analyzing complex urban networks. In metro cities, congestion of traffic is the most accepted transport issue.

Huge traffic jams can affects in different ways like delays, unknown time of travel, maximization of fuel consumption as well as road rage. For instance, the aggregated delay in travel time was nearly 13 billion hours from the year 2010 to 2014, which makes use of nearly six million tons of excess fuel in metropolitan areas in the US (Texas A and M Transportation Institute). Numbers of countries makes utilization of Intelligent Transportation Systems (ITSs) for giving integrated road traffic related services. ITS centrally gather all information and also stores the same information known as traffic sensor data which is collected from multiple heterogeneous sources which are concentrated on real-time traffic data to show the issues by traffic congestions. The traveler as data website of Seattle gives real-time traffic cases as well as time to travel via the city. Many of the traffic data services are depending on information gathered from ITS system.

Continuous historical traffic sensor information is created only one time the real-time utilization of this information is complete. By making utilization of stored historical traffic data, a designer had taken it as important information, like travel time predictions, traffic bottleneck analysis, and survival analysis. Peoples of metro cities may have various queries related road traffics like, what kind of traffic events may have on the road last week? Or which road links are the most rushed on a specific day? For providing such questions there is a need to specifically study the traffic data proposes the requirement for an interactive traffic query framework which assumes a key part in semantic applications for smart cities. As networks in an urban area are extending, the extent of the accessible and constantly monitored traffic data is growing.

Hence, the calculation of potential correlations within data becomes computationally expensive. To this end, new methods for adequately overseeing substantial volumes of available traffic information in a reasonable time are required for enabling efficient travel time prediction capabilities. This motivates to propose a travel time prediction technique that deploys a novel algorithm for the reduction of the required time and the associated computational resources for the calculation of traffic dependencies in large volumes of traffic data.

II. REVIEW OF LITERATURE

In paper [1] authors developed a travel time analysis and prediction model mainly for urban road traffic sensors information depending on the change point analysis algorithm and ARIMA model. At start time series of travel time parameters are clustered by making use of change point mining algorithm then the traffic sensors information pre-processing. After that, a travel time prediction model was created depending on ARIMA model

In paper [2] authors have explained the implementation of a predictive model for vehicle journey time on highways. Authors have also designed the spatiotemporal distribution of travel times by utilizing local linear regression. Authors used real-time data which is very specific for small traveling. For optimizing balance, they made use of local linear regressions for historical and real-time information. The main aim of the authors is the to upgrade the local linear model with greater order autoregressive travel time variables, known as vehicle flow data as well as density data.

In paper [3] authors given a different case analysis of transit period for personal cars as well as heavy goods vehicles is predicted having data driven, the hybrid method by making use of previously stored traffic data of the total high-ranking Austrian roads. While studying data related to the traffic is provided, travel time is predicted using kernel predictor searching for same speed density pattern. If the case of missing data of the traffic travels time is predicted with deviations from typical historical speed time series. The steps taken in pre-processing of traffic data the hybrid prediction technique and the outcomes for a selection of chosen road are given.

In paper [4] authors have developed Least Squares SVM (LS-SVM) technique which supports the training process by clarifying the quadratic programming issue by making use of the prediction outcomes a Genetic Algorithm (GA) is utilized to find the optimal set of model parameters. The GA depending on LS-SVM method is tested utilizing current travel time information from a bus route in Melbourne, Australia.

In paper [5], authors have developed novel prediction technique by implementing the particle filters algorithm. Different traffic parameters of the highway are gained depending on the interval velocity measurement framework as well as created a state model with the help of gained association parameters for travel time estimation. Then the Bayesian theory is used for simulating probability of the system state. Developed technique adopts the system state transition model depending on the history information retrieved from interval velocity measurement system also the use of particle filters maximizes the developed technique for handling of dynamic as well as the uncertainty of the framework.

In paper [6] authors have developed personalized online travel time prediction model is presented. The developed system concentrates on urban road traffic problems from individual commuters perspectives. The system is able to find the critical prediction factors which may lead to high prediction accuracy depending on a proposed prediction effectiveness function. Personalized prediction is performed at the time of getting high accurate prediction outcomes consolidated with prediction lead times are used to personal computers.

In paper [7] authors developed a Markov transfer matrix for predicting the traffic state, as well as put the estimated state value into the joint distribution of bus travel time as well as state, the real-time bus travel time forecasted value can be retrieved. The forecasted bus travel time of the system assessed with information of transit route 69 in Guangzhou between two bus stops.

In paper [8] authors are making an attempt of forecasting to predict travel time by consolidation of VD and PV data sources by a dynamic weighted fusion system. The weights of the data sources are runtime calculated by the distance weight system for maximizing the accuracy of the prediction. Developed TTP model is used to a small traffic network located in the east and north district of Tainan City, Taiwan.

III. EXISTING SYSTEM

In the existing system parametric techniques are based on specific models whose general structure has been characterized ahead of time and just the correct values of a given set of parameters need to be determined. The learning system, by which these parameters are set, is actualized heuristically on the basis of the available data that refer to the historical behavior of the system. The most widely recognized strategies for this kind are created using time series analysis, i.e., Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA)[1] and Space-Time Auto-Regressive Integrated Moving Average (STARIMA)[1]. The existing framework implemented a parametric state-space method with a specific end goal to model traffic flow. An extension to this system is target at dealing with various shortcomings of the classical STARIMA, such as the supposed stationary of the system and the constant relationship among the neighboring links. On the other hand, the term non-parametric is not used in order to indicate the nonappearance of parameters, yet rather to underline the case that this class of travel time prediction techniques does not presuppose a particular model structure. Consequently, both the correct model structure as well as its parameters should be determined while the training phase of the model. Non-parametric strategies can be characterized into two general categories: model-based as well as memory-based. Model-based methods exploit the available historical data only during the training procedure, in order to build the model and define its parameters. After the model is built no additional use of historical data is necessary.

The most prominent memory-based prediction method is non-parametric regression mainly represented by the k-Nearest Neighbour (kNN) technique. The introduced the kNN tech-nique and proved that it outperforms both the naA ve method of HA and the parametric ARIMA model in terms of ro-bustness against variable datasets. Still, system demonstrated that the results obtained through Seasonal ARIMA modeling exceed the precision of the kNN.

IV. PROPOSED SYSTEM MECHANISM

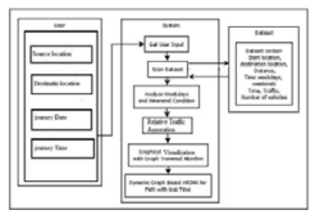

Fig. 1. Proposed System

Figure 1 shows Proposed System. In this system introduces a graph based approach for regulate spatial dependence between roads of the identical network. In particular, after representing the traffic network as a graph, the local neighbours of each road are extracted using modified graph traversal algorithm and a lower complexity variant of it. A Pearson product a moment correlation-coefficient-based metric is applied on the selected graph nodes for a already stated number of level sets of neighbours.

Modules:

1) User Interface:

In this module user can give input to the system. User selects the source and destination location to get shortest time path. The user interface provide number of other option like user want to travel time for current time or another time. User can give input as journey data and time.

2) Relative Traffic Aggregation[1]:

The detection of traffic correlations between roads in a city network can result in better prediction . Usually, the relative traffic aggregation[1] between roads are estimated in terms of proximity. In this context, a distance , e.g. the Euclidean distance is used rendering the most correspond roads for a road of interest among those which are closer to it. This concept is expanded where the mutual relationship are estimated in terms of traffic status, rather than proximity. For example, the huge traffic of a highway at current time can influence the traffic of other roads that do not about to it, in the future. Such correlations are explored using a Pearson product-moment correlation coefficient based standard measure known as Relative Traffic Aggregation[1].

The latter is applied between any pair of roads in the network resulting in neighbours that are not necessarily geographically close to each other, but share similar traffic patterns. Relative Traffic Aggregation describes the correlation between the present (future) values of the traffic time series of a road of interest, and the past (present) values of the series of another road within the network.

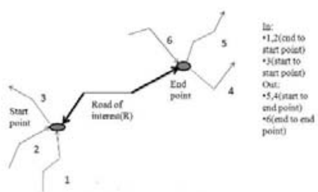

Fig. 2. Relative traffic aggregation & Graph visualization

3) Graph visualization:

In order to deal with the computational complexity of the Relative Traffic Aggregation computations, Namely to reduce the computational time, the following principle is applied. Since every road of the network is either one way or bidirectional, the in and out roads for a road of interest are defined. The in roads are those that end to the start or end point of the road of interest, whereas the out roads are those that start from these points. The inroads import traffic at the road of interest, whereas the out roads export traffic. This shows in Figure 2. Based on this concept the urban network is represented as a geometric directed graph, in which every node represents a road and every edge a straight in or out connection. The adjacency matrix A of the graph is given in figure 3. The non-zero elements in row i of the adjacency matrix represent the out connections to a road i and those in the respective column the in connections. As per noted that roads allow traffic in both directions are considered both in and out. According, the corresponding adjacency matrix of the graph represents all the first order connections (neighbors) between roads in the network.For graph representation we use Jung Tool. The Java Universal Network/Graph Framework is a software library that provides a common language for the modeling, analysis, and visualization of data that can be represented as a graph or network. It is written in Java, which allows JUNG tool based applications to make use of the huge built-in ability of the Java API, also those of other existing third-party Java libraries

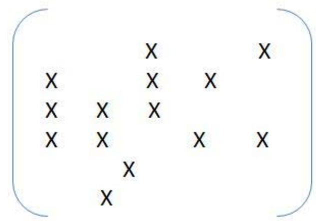

Fig. 3. Adjacency matrix graph

4) Dynamic Graph based ARIMA[1]:

In this module ARIMA is prediction model[1]. ARIMA is time series analysis model. It predict future value with help of past value. AR use for predict value. MA use for error correction. I indicate integration. With help of source and destination , relative dynamic traffic between them the ARIMA model finally calculate shortest time path. Finally user get shortest time path from source to destination location.

V. ALGORITHM USED

1) Start
2) Read source, destination and journey date, time
3) Find source and destination in datasets and paths (mod-ifying graph traversal)
4) Modified traversal[1] (u; A; l_s)
   a) N = {u}

      /* u=vertex , A=non zero elements in adjacency matrix, N=number of nodes in graph, Is=level set of vertex u */
   b) Mark u as visited
   c) For i = 2 : l_s in parallel
   d) B = {}
   e) For all v in N
   f) B = B ∪ {A_v}

g) End for
h) N = N ∪ B
i) End for

5) Calculate shortest time path using Dynamic graph based ARIMA[1]
6) Get shortest time path
7) End

VI. EXPERIMENTAL SETUP

The system is built using Java framework (version jdk 6)on Windows platform. The Netbeans (version 6.9) is used as a development tool. The system doesnt require any specific hardware to run; any standard machine is capable of running the application. Then we have to setup datasets. In this dataset contains the source location, destination location, time, distance and no. of path. The datasets also contain traffic data. It contain number of vehicle in road. The traffic data is time variant data. In traffic data also contain number of roads and highways and number of lane of road. The dataset divide into to part one is week days and another is weekends days.Data is observed of pune city with help of google map. Ten weeks data collected from google maps. The traffic pattern is varies for week days and weekends days. Datasets is store in csv format. Data is fetch using java library. Then system install java tool called as Jung tool for database access and graph generation and representation. System use java universal network graph/framework (Jung) tool which is java library for representation of graph. Jung tool is open source library. It provide language for modeling, analysis and visualization of data that represent as a graph or network. Different algorithm like graph theory, data mining, social network analysis ,routines clustering for decomposition ,optimization and random graph generation are implemented using Jung tool. Reading and updating neighborhoods of an object or node. Apart from an object-oriented API to graph database, working with node , relationship and paths objects, it also offer high speed transversal And graph implementations.

VII. RESULT AND DISCUSSION

In this, system give the best low traffic path between source and destination and time required for traveling. In figure 4 green is path suggested by the system. And also show the travel time.

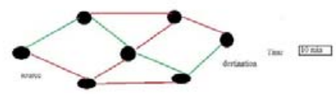

Fig. 4. shortest time path(green)

In this section compare locations with response time Table 1 shows the response time.

The algorithm’s response time should remain stable as no of nodes between source to destination increase rapidly. This is assured using multithreading approach for path detection between source to destination.

The scalability of the algorithm assured by using the parallel algorithm.The system can be implemented in share memory architecture to achieve parallelism .

In this section, presented the evaluation of proposed system. With help of System shows the different results and graph. The different graph and results according to the traffic of week days and weekends day.

First system shows the number of locations versus re-sponse time. Following Graph shows the as number of lo- cations increase change in response time. Show the time for 100,200,300,400,500,600 locations.

In this section compare source and destination with response time. And also compare time for number of hopes increase in path. Table 1 and fig.5 shows the response time.

TABLE I
NUMBER OF LOCATIONS VS RESPONSE TIME

Serial No.	Number of Locations	Response Time in Ms
01	100	1100
02	200	2200
03	300	3300
04	400	4400
05	500	5600
06	600	6700

Fig. 5. Number Of Locations vs Response Time

B. Traffic Analysis At Weekdays

System shows Travel time How travel time predication vary from morning, afternoon and evening section. Also check for week days and weekend days traffic. System take source as shivaji nagar and destination as karve nagar and shows varies time.Fig.6 shows the time required to travel from Shivaji nagar to karve nagar at morning section.Fig.7 shows The number of Hops versus Response Time. At the Morning Section of weekdays.Fig.8 shows the time required to travel from Shivaji nagar to karve nagar at afternoon section.Fig.9 shows The number of Hops versus Response Time. At the Afternoon Section of weekdays.Fig 10 shows the time required to travel from Shivaji nagar to karve nagar at Evening section. Fig. 11 shows The number of Hops versus Response Time. At the Afternoon Section of weekdays.

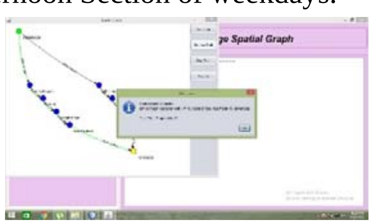

Fig. 6. Time Predication At Week Days Morning

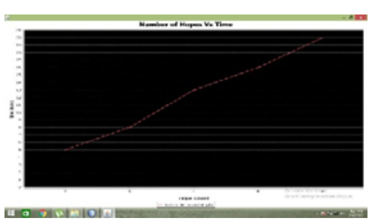

Fig. 7. Number of Hops versus Response Time

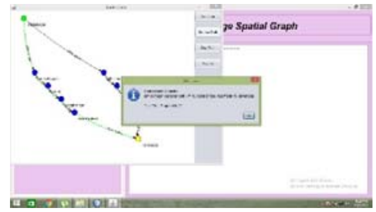

Fig. 8. Time Predication At Week Days Afternoon

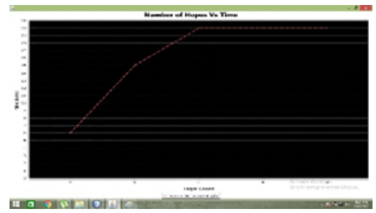

Fig. 9. Number of Hops versus Response Time

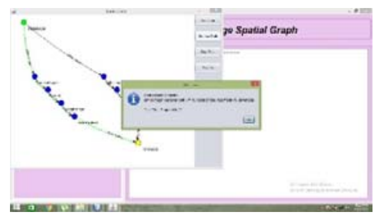

Fig. 10. Time Predication At Week Days Evening

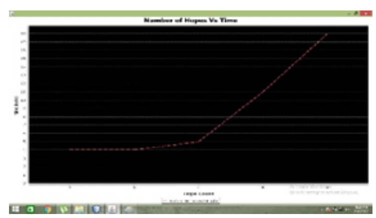

Fig. 11. Number of Hops versus Response Time

VIII. TRAFFIC ANALYSIS AT WEEKENDS

Next section discuss about weekend traffic. Weekend days Shivaji nagar and karve nagar more traffic then week days .so it required more time then week days. Fig. 12 shows
The number of Hops versus Response Time. At the Morning Section of weekend days.Fig.13 shows The number of Hops versus Response Time. At the Afternoon Section of Weekend days. Fig.14 shows The number of Hops versus Response Time. At the Evening Section of Weekend days.

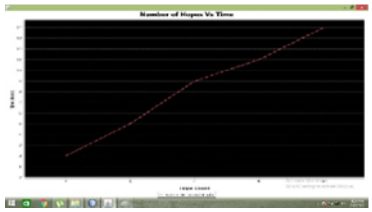

Fig. 12. Number of Hops versus Response Time At Morning

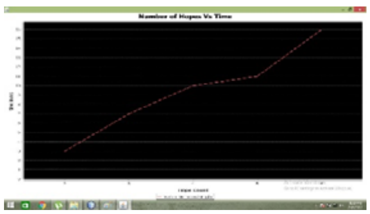

Fig. 13. Number of Hops versus Response Time Afternoon

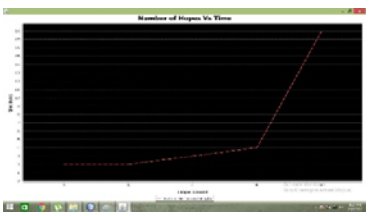

Fig. 14. Number of Hops versus Response Time at Evening

A. Discussion

In this section, system shows the traffic vary in term of time. For this, system observed the four source to destination location to find change time with respect to week days, weekend day ,morning, afternoon,evening. Some path have same traffic in both week day and weekend days. Some path have different traffic in different days. Fig.15 shows this traffic variation with help of graphs.

Fig. 15. Traffic Variation

IX. FUTURE SCOPE

1) Database building for decision making can be enhanced with integration with GPS. So we can use live data.
2) We can define types of vehicle in datasets.
3) Improvements in the implementation of Graph traversal and relative traffic aggregation setup might reduce com-putation times for path and increase accurate travel time and path.

X. CONCLUSION

Newly introduced Dynamic graph based ARIMA[1] prediction method is suitable for calculate travel time in big traffic data, such as Pune city. In particular, it significant improved performance on the computation of the relative traffic aggregation between roads of the same network. Compared to the this approach. When the proposed approach is used for computational complexity reduces from $O(N^2)$ to $O(aN)$; with a > 1:

A practical implication of the dynamic graph-based ARIMA[1] approach is that it enables the study of traffic dependencies between roads in urban networks for improving traffic prediction and maintaining computational performance for traffic relation in large networks. This enhancement intro-duced by Dynamic graph based ARIMA[1] is mainly related to the application of the Modify graph transversal.

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