IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-7, Issue-9, Sept 2019 E-ISSN: 2347-2693

# A Comprehensive Study of Route Prediction Algorithms

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DOI: https://doi.org/10.26438/ijcse/v7i9.7885 | Available online at: www.ijcseonline.org

Accepted: 10/Sept/2019, Published: 30/Sept/2019

***Abstract*—** The position of an individual on Earth is of great importance and can have enormous applications such as Route Recommendation, Driving Navigation, Vehicular Turn Prediction, Travel Pattern Similarity, Pattern Mining, Route Planning, Social Networks, Vehicular ad-hoc networks and so on. Trying to figure out where you are and where you are going is probably one of man's oldest pastimes. Route Prediction is also dealing with the same thing. There are many attributes, for example, temporal attributes, and transportation means, which can also be used for predicting next optimal point towards the destination. Over the years, all kinds of technologies have tried to simplify this task such as Landmark Techniques, Dead Reckoning Technique, Celestial Techniques, OMEGA Technique, LORAN Techniques, Satellite Navigation Technique and so on. This paper gives a detailed survey of some recent algorithms of route prediction, the attributes handled by them and the methods used by them.

***Keywords*—** Data Mining, Route Prediction, Probabilistic Model, Route Predictor Systems, GPS, Route Pattern, Map Matching, Spatial Database, Trajectory

## I. INTRODUCTION

In day to day life, most of us repeat our journey, for instance, a student goes from home to auto stand, auto stand to metro station, metro station to school. When classes over, he travels from school to metro station, metro station to coaching. After coaching classes, he travels back to auto stand and then from auto stand to home. This is the one-day trajectory of that student, which he generally follows during the weekdays. Suppose that student is at home then his next predicted destination would be auto stand. As he reached the auto stand, the next predicted destination would change to the metro station. After the metro station, the next destination point would be school and so on.

Route prediction is dealing with the prediction of the next destination point towards the destination. It plays an important role in our day to day life, for example, intelligent transportation system [1],[5] in which route can be accessed in advance, route-specific traffic information [11] can be provided and better route advice [12],[21],[22] can be given to drivers. Fuel Consumption can also be reduced and a better way of traveling can also be provided by Eco routing [14]. Researchers from Nissan Motor Company Limited (A Multinational Automobile Manufacturer) [9] have shown that if in advance, the vehicle route was known, the hybrid fuel economy can be improved by up to 7.8%. The optimal control scheme for a hybrid, assuming the route is already known, has also been explored by Tate and Boyd [15]. The other applications of route prediction are vehicular ad-hoc networks [5],[6], traffic congestion estimation [5],[6],[7], resource prediction in grid computing [5],[6],[8], navigation system [7],[18], recommendation system [19], transportation system [20] and so on.

The route patterns of people can be learned by using Global Positioning System (GPS) logs [2]. To predict the route of a user, the data from different individuals are collected using Smartphones [1],[2],[3] and Personal Digital Assistants (PDAs) [1]. Data contain the location traces of different individuals at different instances of time. The smartphone incorporates powerful sensors [2] that collect the trajectory of an individual. Trajectory is represented as $(L1_0, L2_0, t_0)$, $(L1_1, L2_1, t_1)$, ... , $(L1_n, L2_n, t_n)$ where $(L1_k, L2_k, t_k)$ is the user's location at time $t_k$ where $0<k<n$ . The Trajectory may contain redundant data. Before doing the route pattern mining, the redundancy is removed from it. And finally, the route for an individual is predicted using historical data.

Many researchers have worked on methods and algorithms for the prediction of the user's route. In this paper, different existing methods have been discussed. The methods have been compared with each other to have future aspects in the discussed area.

Rest of the paper is organized as follows, Section I contains the introduction of route prediction, Section II contains the detailed survey of some recent route prediction methods and

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algorithms, Section III presents a comparison study of different techniques and algorithms with future directions and Section IV concludes the research work.

## II. RELATED WORK

Ling Chen et. al. [1] proposed a Client-Server Architecture and two Prediction algorithms to provide offline and online Route Prediction during the journey. Fig. 1 shows the Client-Server Architecture. Client-Server Architecture incorporates three modules. Data Preparation Module is the first module of this architecture. The second module is the Mining Module. And the last module of this architecture is the Personal Route Prediction Module. In the first module, the raw trajectory data is collected by using GPS devices and outliers from the raw data are removed by using five specially designed data filters. The five data filters are Duplication filter, Speed filter, Acceleration filter, Total distance filter, and Angle filter. The filtered data obtained from the previous step is segmented into trips. In the second module, Continuous Route Pattern Mining (CRPM) algorithm is applied for pattern mining. The basic route mining algorithm and the heuristic route prediction algorithm are the two decision tree-based Prediction algorithms that are used to predict route in the third module. They have focused on the prediction of the route of individual people rather than the route of a vehicle. They have conducted the experiments with a data set of 17 individuals collected during one month.

Je-Min Kim et. al. [2] proposed an approach to predict the current route of a user, using a probabilistic graphical model built from historical data. Fig 2 shows the architecture of Probabilistic Graphical Model. It incorporates the following sequential parts. Firstly, the collected routes are segmented into trips using heuristic algorithm. Secondly, it abstracts the route pattern of users from personal GPS histories using image processing. This is known as route mining. Thirdly, transition probability and conditional probability are calculated to remove overlapped segments and to predict the route. For this, two models are built namely Transition Model and Observation Model. Transition Model calculates the transition probability between the segments. The Transition Model is represented by (1):

$$P(s) = P(s \mid s_i) = \prod P(s_i i \mid Prev\ s_i) \quad (1)$$

where, s = current segment of user, ( $s_1, s_2, s_3, \ldots, s_k$ ) = series of segments, $s_0$ = next segment predicted by joint probability that the user will visit, $P(s, s_i)$ = probability that $s$ and $s_i$ is visited by person.

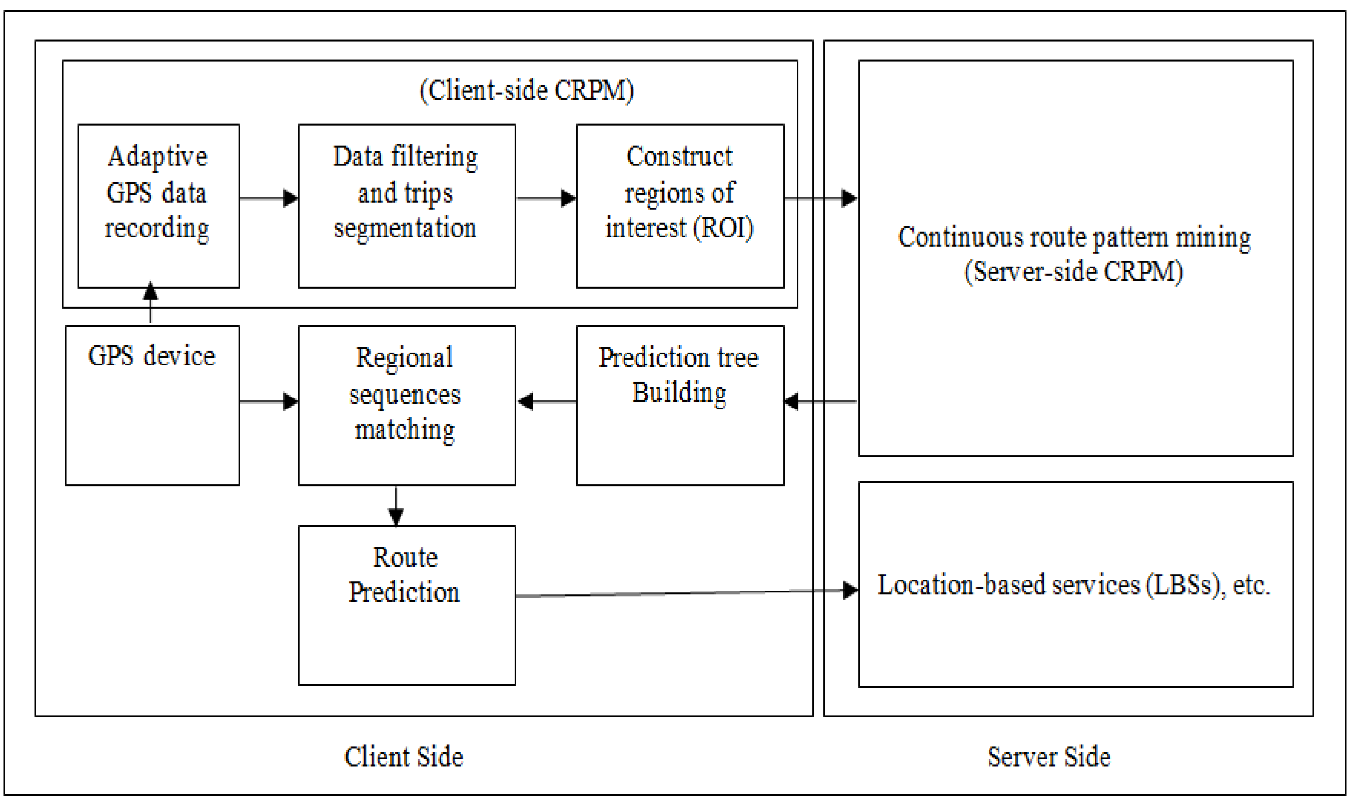


Fig. 1. Client-Server Architecture

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Observation Model calculates the conditional probability between a segment and set of environment facts. The Observation Model is defined by (2):

$$P(\,s, o_1, \ldots, o_n\,) = P(\,s\,)\prod_{i=1}^{n} P(\,o_i\,|s\,) \qquad (2)$$

where, $s$ = user's current segment, $(\,o_1, o_2, o_3, \ldots, o_k)$ = series of environmental variables such as time of day, day of week, weather, behavior, $s_0$ = the prediction of next segment, determined by probability of each $o$ and the conditional probability for each $o$. $P(s \mid o_i)$ = probability that $s$ and $o_i$ occur.

Mingqi Lv et. al. [3] proposed a mining framework to predict the route from personal trajectory data. It adapts the high degree uncertainty of personal trajectory data. Trajectory abstraction and frequent pattern mining are the two constituents of this framework. Firstly, the GPS data is preprocessed which involves preprocessing of trajectory. Trajectory Preprocessing consists of three parts.

First, the cleaning of data takes place i.e. removing the outliers from the trajectory data. Second, the reconstruction of trajectory data takes place that segments the trajectory into different trips with definite source and destination. Last, compressing the trajectory data and transforming them from the point-based trips to line based trips. Secondly, trajectory abstraction discovers the common sub- segments from the

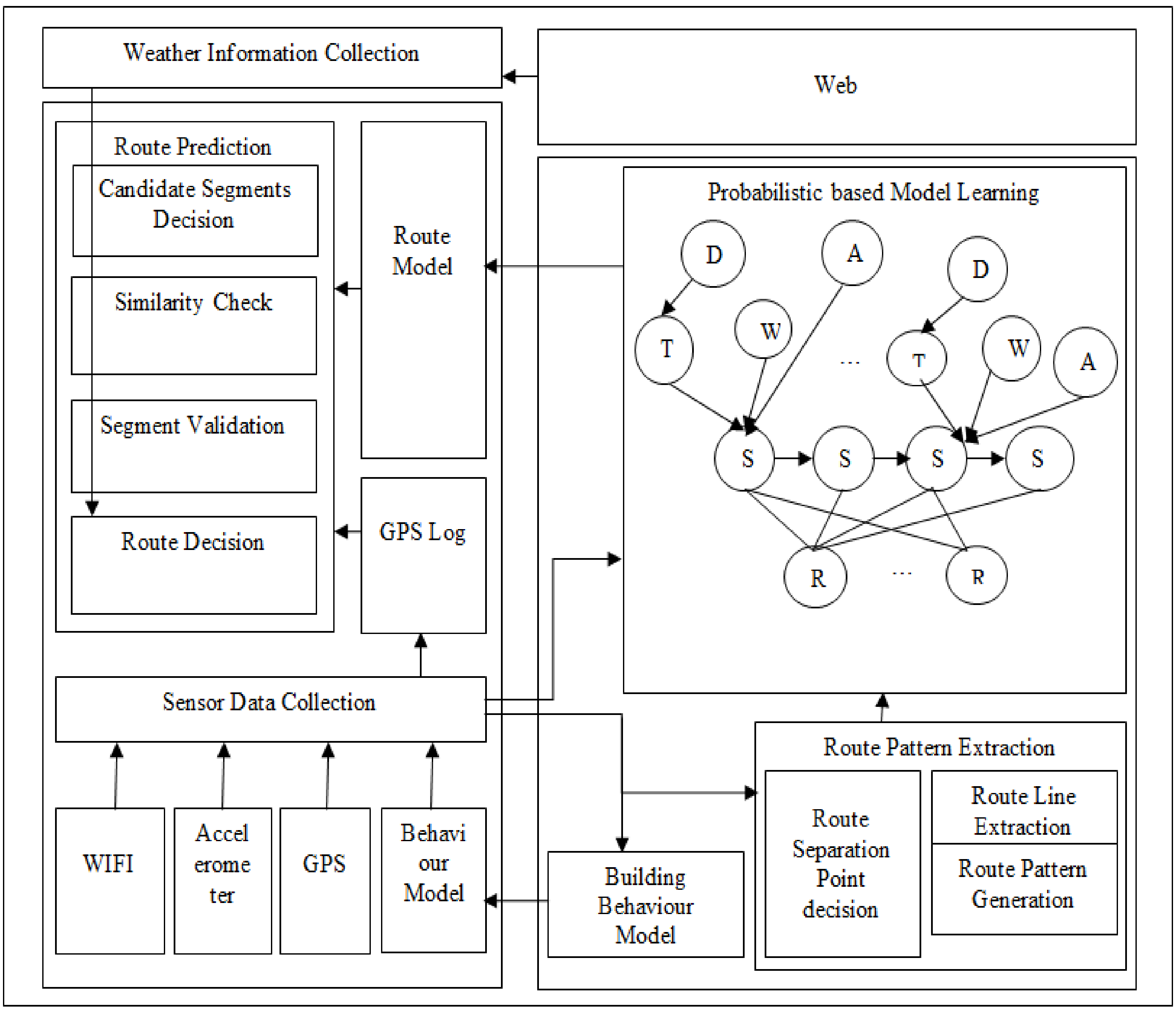


Fig. 2. Architecture of the Probabilistic Graphical Model

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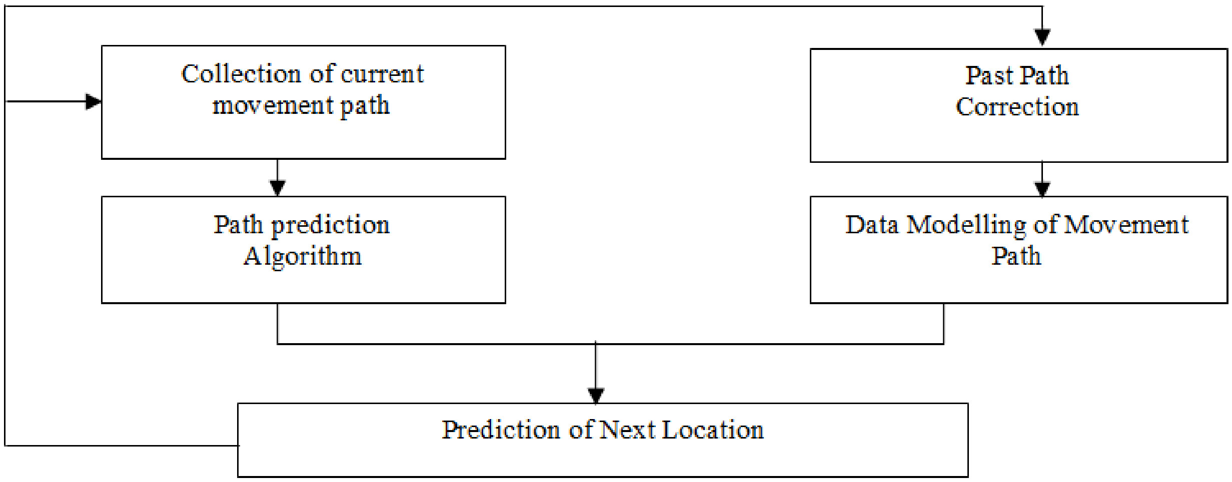


Fig. 3. Path Prediction Flow Chart

trajectory data by using group and partition approach. After trajectory abstraction, the framework extracts route patterns based on the Spatial Continuity based Pattern Mining (SCPM) algorithm, which takes into account the spatial continuity property of elements in route patterns to generate longer and more complete patterns of the route.

Seongwon Min et. al. [4] proposed a real-time path prediction and grid-based model to predict pedestrian path. Fig 3 shows the flow chart of the proposed method. This method uses the Recursive Least Square (RLS) algorithm to estimate the next location of the individual using GPS logs. It can predict the path of the unspecified person in vehicle to pedestrian (V2P) environment. They applied the RLS algorithm to GPS data. GPS data consists of latitude, longitude, speed and direction of a person. After applying the RLS algorithm, a predicted path is obtained. But it can be seen that the following algorithm works well for linear prediction and the error rate is significantly high when the direction of the measured GPS and the pedestrian is different. To reduce this error-rate of curve prediction, author proposed a grid based method. The collected path is divided into grid by grid-based method. Now the path is available in the grid and transforming the path of each cell into equation and use (3) and (4) to eliminate error caused by GPS delay.

$$\text{If } d_{avg} * 0.9 > d_p \quad or \quad d_{avg} * 1.1 < d_p \tag{3}$$

$$\begin{pmatrix} L'_{pn\ about\ n\rightarrow lon} \\ L'_{pn\ about\ n\rightarrow lat} \end{pmatrix} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \begin{pmatrix} L_{pn\ about\ n\rightarrow lon} \\ L_{pn\ about\ n\rightarrow lat} \end{pmatrix} \tag{4}$$

Vishnu Shankar Tiwari et. al. [5] have focused on building a route prediction application that is end-to-end horizontally scalable. It comprises of two steps. Firstly, the collected raw GPS traces are converted into trips by map matching. Secondly, all the suffixes with their frequency of occurrences are calculated. Lastly, it builds a probabilistic generalized suffix tree to predict the route of an individual. Road network spatial data sets and GPS traces of users, collected and distributed by Microsoft under the Geolife project, are used by them. This data was collected by 178 users for around four years & mainly from the Beijing area of China. In this paper, Hbase (open-source non-relational distributed database) is used for storage and map-reduce framework for performing map matching.

Vishnu Shankar Tiwari et. al. [6] proposed a Context Tree Weighting (CTW) model which is probabilistic in nature. Context Tree Weighting (CTW) is widely used in various applications in the area of data compression and machine learning [10]. To construct Context Tree Weighting (CTW) model, time stamped GPS traces are collected over a long period of time. Then GPS traces are broken down into smaller units called trips [13]. Trips mapped to road network graph using map matching process which identifies the object locations on road network graph. Map Reduce computation framework is used for its implementation.

Shun Taguchi et. al. [7] proposed a novel online map matching method with route prediction. The proposed map matching method predicts future routes by using the probabilistic route prediction model and the estimated route is then updated by the observed trajectory. The main idea of this method is to replace future GPS points with a probabilistic route prediction model. In this method, the candidate of $r_k$ is predicted from the previous route $r_{k-1}$ by using the route prediction model, then $r_k$ is updated and determined by using an observation model with a current observation $g_k$. The route prediction model is based on a Markov model that describes route transition probability $P(\ r_{k+1} \mid r_k\ )$. The route transition probability is represented by (5).

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$$P(\ r_{k+1}\ |\ r_k\ ) =\ \sum_{\tau} P(\ \tau\ )P(\ r_{k+1}\ |\ r_k\ ,\ \ \tau\ )\ \ (5)$$

where, p(τ) is the edge transition probability $P(\ e_i\ \rightarrow\ e_{i+1}\ )$ represented by (6) & (7).

$$P(\ \tau\ ) =\ \prod P(\ e_i\ \rightarrow\ e_{i+1}\ ) \qquad (6)$$

$$P(\ e_i\ |\ e_j\ ) = \frac{N(\ e_i \rightarrow e_j\ ) + 1}{\sum N(\ e_i \rightarrow e_j\ ) +\ N_j} \qquad (7)$$

where $N(\ e_i\ \rightarrow\ e_j)$ is the number of transitions from $e_i$ *to* $e_j$ in the training data and $N_j$ is the number of road segments connected from $e_i$.

GPS observation probability $p(\ g_k\ \mid\ r_k)$ is modeled as (8):

$$P(\ g_k\ |\ r_k\ ) =\ \int_0^{r_k - 1} \frac{1}{\sqrt{2\pi\sigma_g}}\ exp\left(\frac{\text{dist}(\ g_k\ , x)^2}{2\sigma_g}\right)\ P(x) \qquad (8)$$

In (8), $dist(\ g_k\ ,\ x\ )$ is the Euclidean distance between $g_k$ and $x$ on a road segment $r_k$ and $\sigma_g$ is the variance of the observation error. This model significantly improves the accuracy of online map matching without any latency, unlike the Hidden Markov Model (HMM) based approaches that uses future coordinates, which is a notable advantage for real-time applications.

Sudhir Kumar Adlakha et. al. [8] proposed a source to destination application. This application is probabilistic in nature. They have used GPS data points from GPS trajectory dataset collected in Geolife project. Microsoft Research implemented this Geolife project. The dataset contains the location traces of user, segmented into trips. These trips are in the form of location points $(\ x_t^x,\ y_t^x,\ t^x\ ),\ \ (\ x_t^{x+1},\ y_t^{x+1},\ t^{x+1}\ )$ $,...,\ (\ x_t^k,\ y_t^k,\ t^k\ )$.

These location points are converted into set of edges $e_k$, $e_{k+1}$, $...$, $e_{k+m}$ by using Map Reduce Framework. Map Reduce is a programming technique which splits input data into chunks to be executed parallel in distributed systems. The process of mapping points on to network edges is known as Map Matching. In it, each and every journey is digitized to road network i.e. data coordinates are mapped to road network edges [13],[23],[25]. Examining each and every location of user is the main purpose of this method [5],[16-17],[24-25]. A function used for the Implementation of map matching is given by (9).

$$f\big((x_1, y_1, t_1), (x_2, y_2, t_2), \dots, (x_n, y_n, t_n)\big) \rightarrow\ S \qquad (9)$$

where, sequence $S =\ \ e_{i\ ,}\ e_{i+1\ ,}\ \dots\ ,\ e_{i+n}\ \epsilon\ E,\ E$= the edges of the road network.

This mapping of data on single network edge reduces the database size. Finally, they implemented a probabilistic generalized suffix tree with the help of mapper and reducer module to predict the route of a person in a distributed environment.

## III. COMPARISON STUDY

The route prediction system provides the route that a person can take to commute. Different methods and techniques related to this have been studied in the previous section. In this section, a detailed comparative study of those methods has been presented and is tabulated in Table 1.

Table-1: Comparison Study of Different Route Prediction Algorithms

| Year | Author | Methodologies | Outcome | Pros | Cons |
|---|---|---|---|---|---|
| 2011 | Ling Chen et. al. [1] | Client Server Architecture<br><br>Continuous Route Pattern Mining (CRPM)<br><br>Basic & heuristic Tree Based Prediction Algorithms | Extracting longer routes as compared to traditional substring methods.<br><br>Precision of one step prediction is greater than 71%.<br><br>Provides Levenshtein distance of 30% shorter than Markov Model Based Method. | Maintaining Privacy and providing data security.<br><br>Reduces computational load on mobile devices. | Information like temporal attributes, transportation means are not considered to improve the performance of the system while predicting the person route. |
| 2012 | Je-Min Kim et. al. [2] | Image Processing to extract routes.<br><br>Build a State observation model reflecting users’ | Achieved a prediction accuracy of 96.4% in a test performed with 15 smart phone users. | It helps to solve problems with overlapping routes that reflect a user’s intentions | Parameter- sensitive.<br><br>Troubles with routes over short distances. |

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| | | | | | |
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| | | intentions. | | | |
| 2015 | Mingqi Lv et. al. [3] | Spatial Continuity based Pattern Mining (SCPM) | Efficient and effective framework. | It can tolerate various kinds of disturbances in personal trajectory data and can handle a high degree of uncertainty of personal trajectory data. | Not Scalable. |
| 2017 | Seongwon Min et. al. [4] | Real Time Path Prediction and Grid Based Modelling Method<br><br>Recursive Least Square (RLS) Algorithm | Real time route prediction for short distance. | It predicts path of the unspecified persons in Vehicle to Pedestrian(V2P) environment. | Not suitable for long routes. |
| 2017 | Vishnu Shankar Tiwari et. al. [5] | Generalized Probabilistic Suffix Tree (PGST) | Accuracy around 95% achieved. | Reduces Storage requirements and computational time.<br><br>Horizontally Scalable. | Not applicable for new route. |
| 2018 | Vishnu Shankar Tiwari et. al. [6] | Context Tree Weighting(CTW) | It is horizontally Scalable. | Distributed cluster processing time reduces. | During CTW model training phase data was sourced from HBase for distributed processing as that was the most time-consuming process and is a bottleneck in practical implementation. |
| 2019 | Shun Taguchi et. al. [7] | Multiple Hypothesis Technique(MHT)<br><br>Bayesian Filtering | Faster than online Hidden Markov Model(HMM). | Accuracy has been improved.<br><br>Algorithm runs faster for short sampling intervals. | As Sampling rate increases, computation time increases exponentially. |
| 2019 | Sudhir Kumar Adlakha et. al. [8] | Probabilistic generalized suffix tree | Achieving accuracy around 85% . | Horizontally Scalable. | Not applicable for new route. |

A critical look at the available literature indicates the following issues which need to be addressed in future research.

- Prediction systems works well with Short Routes only.
- Methods fail to predict the route of a user for a new destination not presented in databases.
- The collection of data is a very challenging task.
- Scalability is a major concern.

Researcher can work in this direction to build a novel route prediction algorithm.

## IV. CONCLUSION

Predicting the route of a user is a task of great importance. Route prediction is having numerous applications in several domains like VANET, Traffic Congestion, Route recommendation, Route planning, Driving navigation, Social networks, etc. Some authors proposed a prediction model for short or long distance while some authors focused on personal route prediction or driver route prediction but accuracy in prediction is a major concern by all of them. In this paper, a considerable survey on various route prediction methods and algorithms has been carried out. Each of the methods having its pros and cons has been tabulated and can be used to accomplish prediction tasks more efficiently through data mining techniques.

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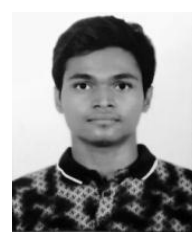

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