Trajectory Clustering for Behavioral Pattern Learning in Transportation Surveillance

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Abstract—The development of an efficient traffic flow monitoring system has been the main focus for many researchers working in the field. Due to the rapid development in urbanization, the complexity of traffic intersections provides challenges for researchers to detect the underlying traffic scenes. With the emerging video-based surveillance system, vehicle trajectory can be extracted for observation and prediction via behavioral pattern learning. Prior to the learning, clustering of the extracted vehicle trajectory data is performed to group the data based on similarity measures. In this paper, the implementation of clustering algorithm on the trajectory data is analyzed and issues concerning the trajectory clustering are discussed.

Keywords – traffic surveillance; trajectory clustering; trajectory learning

I. INTRODUCTION

Traffic surveillance plays an important role in intelligent transportation systems (ITS) in which government has invested heavily invested in. It is indisputable that the rapid development of urbanization due to economic growth requires an efficient surveillance system to collect traffic flow data. Despite that many researchers focused on traffic data in macroscopic scale, it is still crucial to analyze and monitor the microscopic data such as detecting the abnormal behaviors of traffic scene, which enables the determination of the origin of traffic congestion and conflicts [1]. Thus, the challenge of obtaining precise information about the traffic flow at a road intersection such as roundabout is greater.

In the past decades, many computer vision researchers have been working closely to study the pattern of moving traffic at road intersection. This can be performed via observation of traffic flow using vehicle trajectory (tracked point of vehicles) as input data. The traffic flow of a road intersection may contain many statistical information which are of interest to researchers, such as: the traffic volume, left and right turning times, lane changes, as well as the U-turn event counts. With automatic identification of the behavioral information based on a particular road intersection, modeling the traffic flow will be easier as the amount of manually inputted traffic parameter is reduced [2]. However, describing the dynamics of traffic flow via conventional statistical methods still lacks of direct interpretation for human understanding. In the attempt to reduce manual monitoring for traffic flow, behavioral pattern learning from trajectory has been useful to understand surveillance activity.

This paper presents a study of the potential of trajectory modeling with clustering algorithm. The goal of the clustering algorithm is to group common similarities exhibited in a large dataset of trajectory into designated clusters. In preliminary work of trajectory modeling, the retrieval of spatial-temporal trajectory dataset that usually comes in large amount has been introduced through various methods [3]. Although the trajectory query provides labeling task on the raw data for indexing the dynamics spatial-temporal queries, this information is insufficient to provide distinct statistics for dynamic traffic flow. With the clustered trajectory dataset, pattern that describes the maneuver behavior of travelling vehicles at a road intersection can be characterized. Thus, computing similarity measures for the clustering is a primary concerned by researchers. This is due to the inference about the interactions between groups of trajectories are highly emphasized and it is necessitated to compute the measures for the pattern learning task [2].

The organization of this paper is as follows: Review of trajectory extraction from tracking method is presented in Section II. Section III describes the clustering method of the trajectory. The experimental study of trajectory clustering implementation is shown in section IV. Lastly, conclusion is provided in section V.

II. TRAJECTORY EXTRACTION METHODS

In traffic surveillance, trajectory analysis serves as an important and basic research for behavior analysis. It is also becoming the main method used to understand vehicle motion behavior because it is relatively simple and apparent in its interpretation. Generally, trajectory for a vehicle can be defined as a sequence of the vehicle’s tracked points over a period of time as shown in Fig. 1. These tracked points drawn from each action and surveillance activity can be defined with the set of sequential actions [4]. Each tracked point at a particular time instance can consist of the location of the vehicle, which can be either represented as the $(x, y)$ coordinates or distance travelled. The $(x, y)$ coordinates would be preferable as it gives the vehicle’s maneuver (turning angle and direction). The tracked points are reliable data for traffic density analysis as they provide direct and unbiased measurement [5].
A. Vision based tracking. Categorized as: sensor, global positioning system (GPS) and briefly explained here. Three main approaches can be paper, but the approaches of the trajectory extraction are learning of the trajectory are not the primary focuses of this paper.

B. Solely is limited [6]. However, discovering the traffic pattern from these sensors commonly installed at fixed points or road sections. Sensors, inductive loop detectors, magnetic sensors are infrared sensors, ultrasonic sensors, passive acoustic array sensors. Magnetic sensor are commonly installed at fixed points or road sections. However, discovering the traffic pattern from these sensors solely is limited [6].

B. Global Positioning System (GPS)

Another method to probe vehicles for trajectory is through the collected geo-referenced coordinates by GPS receivers. These receivers require road map-matching with the targeted vehicle coordinates. Information of the vehicle speed can be computed quantitatively by measuring the spacing between two GPS tracked points of a specific region on a map [5].

Positioning error may arise and it is a main concern in extracting trajectory based on the GPS devices that provide time and location of tracked vehicles. In fact, the positioning error can be up to tens of meters, which is critical for safety-critical applications.

Many approaches on improving the vehicle positioning accuracy have been widely conducted. One of the prominent approaches is by measuring the inter-vehicle distances. Radio-based ranging methods such as Time of Arrival (ToA) and Angle of Arrival (AoA) are also used to alleviate the positioning error. Although the methods have demonstrated effectiveness in reducing the error, they still heavily rely on complicated techniques with high computational cost, and require additional sensors that are hard to be employed [7].

C. Video Based Vehicle Tracking

Generally this method uses image processing approaches to perform vehicle tracking with the source from video cameras. Well known methods such as Kalman filter, Markov Chain Monte Carlo (MCMC), particle filter [8, 9] are used to track vehicles via estimation of vehicle position based on color and other features that characterize vehicles. Although it is unavoidable that imperfect tracking due to occlusion, low illumination and other disturbances such as image noise resulted from camera vibration may occur, these tracking methods are constantly improved and are robust enough to handle these imperfections.

In general, this vehicle tracking process begins with some image segmentation method, such as foreground/background subtraction [10]. This segmentation excludes unwanted parts that do not belong to the vehicle. Throughout this process, each of the targeted vehicles in the continuous captured image frames is assigned with a particle to perform prediction for future vehicle position. To accommodate the non-linearity of the perspective projection of vehicles, three dimensional bounding box models can be fitted to the target vehicles. Sampling rate of the tracker has to be chosen optimally to eliminate the need of interpolation for the tracked points.

III. TRAJECTORY CLUSTERING

To display the vehicle tracked points, two main representations of trajectory data are commonly used: y coordinate versus x coordinate (spatial) and 3 dimensional (3D) data with x coordinate, y coordinate, and time, t. An example of trajectory representation in x-y coordinates is shown in Fig. 2. As deriving dissimilarity measures on time series are mainly concerned, the trajectory data set in Fig. 2 only portray the trajectory information in real world coordinates. This is inadequate for discriminating the trajectories in time-variant perspective, which is crucial for detailed analysis. Thus, two basic similarity measures, namely: spatial location and time, are used to perform clustering. A trajectory is composed of dataset that contains a sequence of spatio-temporal tracked points as shown in (1). Equation (2) shows a tracked point that constitutes its spatial location \((x_i^k, y_i^k)\) at time instant \(t_i^k\).

\[
T^{k=1,2,3,...N} = \left\{p_1^k, p_2^k, p_3^k, ... p_n^k \right\} 
\]

\[
p_i^k = (x_i^k, y_i^k, t_i^k) 
\]

The trajectory clustering is aimed to group the trajectories into specific route types. Clustering methods such as k-means clustering and fuzzy c-means (FCM) clustering are well known iterative centroid-based clustering typically used for such application. In this paper, fuzzy c-means clustering (FCM) is used for the trajectory clustering.

FCM clustering was introduced by Dunn in 1973 and it was further improved by Bezdek in 1981 [11]. FCM clustering is very similar to k-means clustering, such that it partitions a set of observations into a pre-determined number of clusters. With the computed similarity measures, each observation is assigned to the cluster with the nearest
mean value. FCM clustering converges when the minimization of the objective function is met. Equation (3) shows the minimization of the objective function in FCM clustering, where $u_{ij}$ is the membership of an observed data, $c$ is the cluster centroid (mean) and $m$ is the level of fuzziness [12]. FCM is a soft version of $k$-means clustering, which allows an observed element to belong to more than one cluster, rather than just single cluster in the case of $k$-means clustering. The steps of FCM clustering in general are shown in Algorithm I. The stopping criterion for the iteration of clustering is determined by $\varepsilon$.

$$\min \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \left\| T_r(x_i, y_i, t_i) - c_j \right\|^2, \quad 1 \leq m < \infty \quad (3)$$

**Algorithm I. Fuzzy C-Means Clustering for Trajectory**

1. **MEMBERSHIP FUNCTIONS Initialiseation**
2. Determine the total number of vehicle tracked points, $N$ and number of clusters, $C$
3. Initialise the membership matrix with $U = [u_{ij}]$
4. **CENTROIDS COMPUTATION**
5. FOR $j = 1:C$
6. centroid of cluster $j$, $c_j = \frac{\sum_{i=1}^{N} u_{ij}^m T_r(x_i, y_i, t_i)}{\sum_{i=1}^{N} u_{ij}^m}$
7. **END FOR**
8. **MEMBERSHIP UPDATE**
9. Update $U$ to compute $U_{new}$ with $u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{T(x_i, y_i, t_i) - c_k}{\left\| T(x_i, y_i, t_i) - c_k \right\|^2} \right)^{2/m}}$
10. If $\| U_{new} - U \| < \varepsilon$ then stop, otherwise return to centroids computation step

### IV. EXPERIMENT RESULTS AND DISCUSSIONS

To illustrate the collected trajectory superimposed with an image of monitored scene, a trajectory dataset from Massachusetts Institute of Technology (MIT) is used [13]. This dataset contains 40,453 trajectories of moving objects in a parking lot scene that are captured for five days. As the trajectory dataset is huge and requires a significantly high computation time, only a selected range of trajectories are used. Fig. 3 shows the plot of collected trajectories from two perspectives. Each of the plotted trajectories in blue consists of an array of tracked points. From the Fig. 3, the clustering of the trajectories is necessitated to provide spatial definition by finding trajectories that are identical and grouped together as a cluster.

Results of FCM clustering on the trajectories with different number of clusters are shown in Fig. 4. As the number of clusters is a required input for FCM clustering, choices of three, five and ten clusters are selected. It can be seen that trajectories are successfully grouped into the clusters. However, some of the identical trajectories are classified into different clusters, which resulted in the clusters being split into multiple enclosed regional areas in the scene. This issue become prominent as the given number of clusters is increased. This shows limitation of using FCM clustering for the trajectories. The FCM clustering has a tendency to group observed objects that are convex in shape efficiently. In the case of these collected trajectories, they are in the shape of branches and the tracked points are distributed in diverting manner. This is likely to be the reason why the FCM clustering process has under-performed.

Clustering based on spatiality alone does not reflect the dynamic changes of the moving objects [14]. To reflect on the dynamic changes, another similarity measure (time) is included in the clustering algorithm with the 3D trajectories plot shown in Fig. 5. Clustering results are as shown in Fig. 6. Comparing the results in Fig. 4 and Fig. 6, it can be seen that the inclusion of the time attribute in the clustering algorithm produces results that vary greatly. As the time element provides the sequential order of the tracked points, a trajectory paired with an initial and final tracked point can be secured into the same cluster. In other words, issues concerning a complete trace of trajectory with an array of connected tracked points grouped into more than one cluster can be alleviated. However, in cases where the trajectories are identical in route type (heading straight) but different in tracked directions, trajectories might be grouped to more than a cluster. This indicates that clustering based on spatial-temporal information may not provide the best solution to cater to the requirement of grouping trajectories according to specific route type.

### V. CONCLUSION

Based on the results from the implementation of FCM clustering on trajectory, it can be concluded that trajectory clustering is a necessitated task before performing pattern
learning and prediction for surveillance purpose. Depending on the application purpose in surveillance, defining semantic region can be performed for route and maneuver specification of the travelling vehicles in traffic scene.

The clustered trajectories can potentially provide visualization system of traffic flow. This helps to assist operators in traffic surveillance to reduce manual work in providing traffic parameters for monitoring specific activities such as traffic conflicts that can cause collision. Improvement of the clustering algorithm can be performed by implementing reinforcement learning to aggregate the trajectories in a more efficient manner, and reduce the reliance on accurate tracking on individual vehicles.

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