Vehicle Anomaly Detection based on Trajectory Data of ANPR System

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***Abstract*—This paper proposes a machine-learning technique to detect vehicle anomalies from data captured by automatic number plate recognition (ANPR) system. The proposed anomaly detection technique is specially engineered to exploit both spatial and temporal features of vehicles captured by ANPR system, so as to accurately detect anomaly vehicles. We extensively evaluated the proposed technique using a two-month long dataset collected by a real world ANRP system, which has more than three hundred cameras deployed in a big city of China. The evaluation results show that our technique can effectively detect vehicle anomalies from the huge amount of data collected by the ANPR system. More importantly, our technique significantly outperforms existing schemes especially when the data collected by the ANRP system are noisy due to poor weather condition.**

Keywords—anomaly detects; data mining; sensors data management; intelligent transportation; trajectory analysis

I. INTRODUCTION

In the era of Internet of Things (IoT), huge amount of data are collected from various types of sensors on a daily basis. Among the rich set of collected information, motor vehicle related data attracted a lot of attentions from both academia and industry. Processing and mining the rich set of motor vehicle data has became an increasingly important topic. For instance, in the last few years, China is witnessing a rapid growth of motor vehicles in both the urban and rural areas. The huge number of vehicles on the roads creates big challenges to not only traffic monitoring and regulating, but also to public safety. With motor vehicles are increasingly involved in crimes and terrorist attacks, there is a urgent need for detecting abnormal behaviors of vehicles in time, so that corresponding actions can be taken promptly.

Existing vehicle anomaly detection techniques could be classified into two categories based on the processed data, i.e., vision-based vehicle image processing scheme, and trajectory-based data mining scheme. Vision-based vehicle anomaly detection schemes adopt video image processing technology to identify the abnormal driving activities. Traffic congestion detection is studied in [1]; detecting high risk driving behaviors such as violation of backing off, lane changing, turning, winding, speeding, and running red lights are studied in [2~6]; identifying unusual objects on highway such as pedestrians and bicycles is studied in [7] and [8]. However, applying vehicle anomaly detection techniques to address public safety threats is less studied. How to detect sudden acceleration or cardiac arrest behavior near checkpoints or important institutions are studied in [9]. Vision-based anomaly detection schemes are usually distributed, which independently process data collected from a few roads. The distributed nature of those schemes makes it hard to continuously track vehicle objects and collaboratively detect anomalies from the data collected from thousands cameras.

Trajectory-based data mining techniques first extract spatial and temporal information from trajectories, and then analyze the vehicle behavioral patterns. To collect vehicle trajectory data, many research activities exploited the geo-location information provided by on-board GPS devices. For instance, estimating the speed of taxis is studied in [10]; [11] used GPS information to study vehicle density; [12] used GPS positioning data to detect vehicle speeding behaviors. Exploiting GPS data to detect vehicle anomalies has good precision. However, there are considerable overhead in installing the additional positioning and communicating devices on every vehicle, and later collecting data via networks.

In this paper we propose a new trajectory-based technique for vehicle anomaly detection by using data captured by an automatic number plate recognition (ANPR) system. In an ANPR system, a large number of video cameras are deployed at various locations of an area to capture the license plates of passing by vehicles and automatically recognize their plate numbers. Each of such location is often referred to as an ANPR gateway. The trajectory of a vehicle is the concatenation of a sequence of gateways that captures the vehicle's plate number.

Compared to existing techniques proposed in literature, exploiting ANPR data in vehicle anomaly detection has the following advantages:

- High accuracy in vehicle classification under various non-ideal conditions, such as bad weather, poor light, and congested traffic.
- Low costs of system deployment and maintenance, because of lightweight data collection and processing.
- No need to install any additional device on vehicles.
- Better coverage by monitoring vehicles on almost all roads.

Our scheme consists of two components, which exploit spatial and temporal features of motor vehicles to detect anomalies, respectively. We adopt an empirical methodology

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to fine-tune the thresholds used in these two algorithms. A large scale real world dataset is used to evaluate our algorithms. The thresholds are selected based on extensive sensitivity tests on how the thresholds affect the anomaly detection results.

The rest of the paper is organized as follows. Section II presents the spatial and temporal features used in our anomaly detection scheme. In Section III our cumulative rotation angles around the centroid (CRAC) and distance from the centers of K-mean clustering (DCKC) based anomaly detection methods were established. Section IV presents the performance evaluation results. Finally we make some concluding remarks in Section V.

II. TRAJECTORY FEATURES EXTRACTION

By processing the ANPR data, we could get each vehicle's historical ANPR records. Each record includes the captured time, gateway id of the capturing camera, and the license of the captured vehicle.

After getting the ANPR records, we further apply a few filtering rules to filter out those records about a set of special-purpose vehicles because they are not representative to most other ones. The excluded vehicles include taxis, buses, and police/military cars. A vehicle license plate in China starts with an one-character provincial abbreviation, which is followed by an alphabet letter, and then five digits or alphabet letters. License plates for China's police service, government, and military contain specific characters listed in [14]. Finally we used a one-way Hash function to transform the plate numbers for privacy protection.

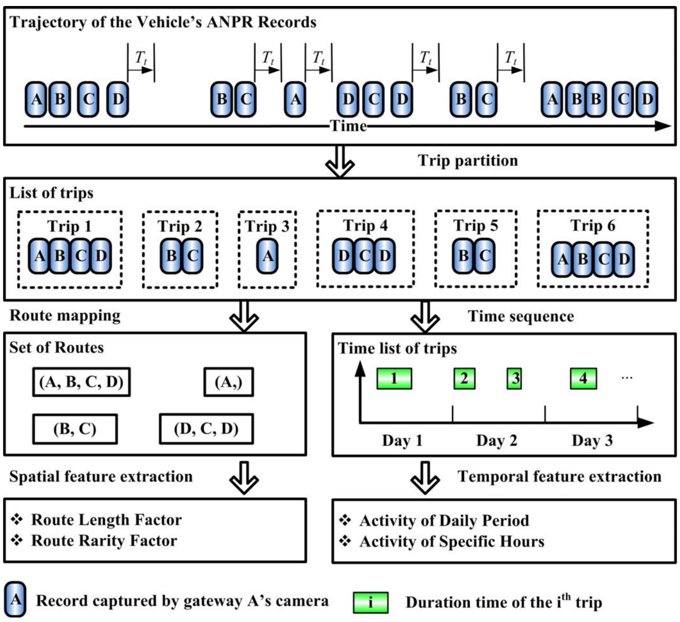

Fig. 1. Trajectory feature extraction example

Next we will discuss the spatial and temporal features extraction from vehicle's ANPR records depicted in Fig. 1.

A. Trajectory Partition

A trajectory is a sequence of multi-dimensional points denoted as $Traj = \{p_1 \ldots p_i \ldots p_n\}$, where each point p_i represents an ANPR record. An ANPR record is represented as p=(*time*, *gateway*, *license*)

Analyzing the entire trajectories of a vehicle might not be able to extract enough features of the trajectory. The whole trajectory Tra_j was partitioned into a set of sub trips, denoted as $Tra_j = \{ trip_1 \ldots trip_i \ldots trip_m\}$, based on the time interval between records. Each sub trajectory tripi indicates an individual short-term driving trip. The time intervals between trips were more than practical *threshold*.

ANPR cameras usually take multiple pictures in a burst when detecting a vehicle's movement, and therefore generate multiple duplicated ANPR data records. We remove those duplicated records in $trip_i$.

B. Spatial Features Extraction

After partitioning a trajectory into multi trips, we extract spatial features from a vehicle's trips as show in Fig. 1.

The path of trip is a sequential tuple of gateways, denoted as $path = (gateway_1 \ldots gateway_i \ldots gateway_k)$. The $gateway_i$ is the camera id of the i^{th} record in the trip. A vehicle v's set of paths is the union of all vehicle v's paths as denoted in (1), where m in (1) is the number of trips. Note that some vehicles with fixed routes, like urban buses and shuttles, may have many trips but only a few paths in set SP.

$$SP_v = \bigcup_{i=1}^{m} \{path_i\} \tag{1}$$

Definition 1 (Route length factor): The length of a *path* is the number of gateways in the *path*. The maximum route length in the set of routes is denoted as $L_{MAX} = \max(|path_i|)$, where $path_i \in SP_v$. The normalized value of maximum route length is the route length factor (RLF), as denoted in (2), which scales all RLF values in the range [0, 1].

$$RLF = \sqrt{\frac{L_{MAX} - 1}{T_{Lenth} - 1}} \tag{2}$$

T_{Lenth} is the length threshold for different dataset. If the region of ANPR system is larger than what the deployed cameras can cover, threstthold T_{Length} should be set a larger value.

Definition 2 (Route Rarity factor): All existing routes could be collected after analyzing all vehicles' trips in dataset. Each route has a set of vehicles that had driven with this route in its historical trips. The route's vehicle set is the union of all vehicles denoted as (3).

$$SR_r = \bigcup_{v=1}^{num} \{v \quad if \quad r \quad in \quad SP_v\} \tag{3}$$

The number of vehicles that had driven among a route indicates the rarity of that route. The rarity of route r is denoted as $rarity(r) = |SR_r|$. The minimum rarity of vehicle v's trips is denoted as $R_{MIN} = \min(|rarity(i)|)$, $i \in SP_v$.

$$RRF = \begin{cases} \dfrac{T_{Rarity} - R_{MIN}}{T_{Rarity} - 1}, R_{\mathrm{MIN}} \leq T_{\mathrm{Rarity}} \\ 0, R_{MIN} > T_{Rarity} \end{cases} \quad (4)$$

And the route rarity factor (RRF) is defined as the normalization of route rarity as denoted in (4).

T_{Rarity} is the threshold value of rarity for normalization. All regular routes with rarity value, which is higher than threshold value, will be normalized to [0,1]. Uncommon routes' RRF values are closer to 1 because there are only a few vehicles had driven among these routes.

C. Temporal Features Extraction

Our ANPR data show that most vehicles have certain temporal patterns. That is, they are active on certain specific dates, or at certain time during a day. We acquire the temporal features of the temporal ANPR records from time list of trips denoted as $T=\{time_1 \ldots time_i \ldots time_m\}$ where the $time_i$ is the capture time of the first record in the i^{th} trip.

The presence list of date is denoted as $fd=[x_1 \ldots x_i \ldots x_N]$, $x_i \in \{0, 1\}$. N is the number of dates during our data collection. If a vehicle presents at the i^{th} day, we have $x_i=1$; otherwise $x_i=0$.

Definition 3 (Activity of Daily Period): The spectral coefficient of Discrete Fourier Transform for the m^{th} wave component of fd is defined as (4)

$$F(m) = \sum_{n=0}^{N-1} f(n) \exp\left(\frac{-i2\pi mn}{N}\right) \quad (5)$$

The magnitude squared of the Fourier coefficients, $|F(m)|^2$, is called the power of $F(m)$. The activity of date period (ADP) is defined as (6).

$$ADP = |F(0)|^2 \quad (6)$$

A vehicle can be active at certain hours, such as the evening hours or commute hours. The presence list of hours is a vector denoted as $fh=[x_1 \ldots x_i \ldots x_m]$, $x_i \in \{0,1 \ldots 23\}$, where m is the number of trips in the vehicle's trajectory.

Definition 4 (Activity of Specific Hours): The presence time count of a vehicle at specific hours, for example from midnight to 6 A.M, is denoted as $Count$. The activity of specific hours (ASH) is defined as (6).

$$ASH = \sqrt{1 - \left(1 - \frac{1}{m} \sum Count\right)^2} \quad (7)$$

III. Centroids Based Classification

Next we discuss how to exploit those spatial and temporal features extracted from trajectories data to detect vehicle anomalies. We propose two anomaly detection algorithms based on the feature vectors presented in Section II: spatial anomaly detection based on the cumulative rotation angle around the centroid, and temporal anomaly detection based on distances from centers of K-mean clustering.

A. Spatial Anomaly Detection

There are two phases in our cumulative rotation angles around the centroid (CRAC) based spatial anomaly detection algorithm. At the first phase, we identify vehicles whose RLF and RRF values are larger than the thresholds. When the RRF value exceeds threshold T_{RRF}, and the RLF value exceeds threshold T_{RLF}, the vehicle would be selected as a candidate vehicle. A candidate vehicle means that the vehicle's driving route is uncommon and the route path is especially long. Therefore, a candidate vehicle is likely to exhibit wandering behavior.

At the second phase, the cumulative rotation angles around the centroid is calculated for each candidate vehicle's trips. In a trip path denoted as path = ($gateway_1$ ... $gateway_i$ ... $gateway_m$), the coordinates of the i^{th} gateway are denoted as (x_i, y_i). The centroid of path, denoted as (x_c, y_c), is calculated as $x_c = (\Sigma x_i) / m$, $y_c = (\Sigma y_i) / m$. The cumulative rotational angle φ around centroid is calculated as (8).

$$\phi = \sum_{i=i}^{m-1} \arccos\left(\frac{(x_i - x_c)\cdot(x_{i+1} - x_c) + (y_i - y_c)\cdot(y_{i+1} - y_c)}{\sqrt{(x_i - x_c)^2 + (y_i - y_c)^2} \cdot \sqrt{(x_{i+1} - x_c)^2 + (y_{i+1} - y_c)^2}}\right) \quad (8)$$

If φ exceeds a certain threshold value Tφ, the vehicle must have the behavior of wandering in the region.

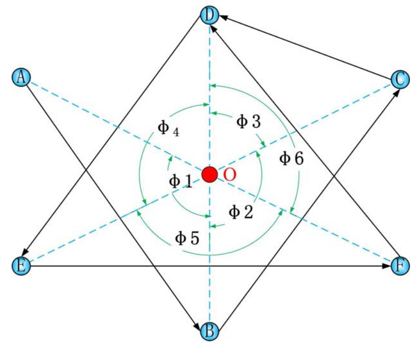

Fig. 2. CRAC for the trip with "A-B-C-D-E-F" route

Fig. 2 shows an example to demonstrate how our spatial anomaly detection works. Here a vehicle is driving among route A-B-C-D-E-F. The centroid of the vehicle's route is O. Then the cumulative rotation angles around the centroid is calculated as $\varphi = \varphi 1 + \varphi 2 + \varphi 3 + \varphi 4 + \varphi 5 + \varphi 6$. If Tφ is 4π and the φ>4π, we determine that the vehicle is an anomaly vehicle with wandering behavior.

CRAC based anomaly detection algorithm is described in Algorithm 1.

Algorithm 1: CRAC based spatial anomaly detection algorithm
Input: *traceDict*: a hash table records all vehicles' trajectory;
vehicleList: a list records all vehicles' number-plate;
routeDict: a hash table records all route's rarity
T_{RLF}: the threshold of the route length factor
T_{RRF}: the threshold of the route rarity factor
T_{φ}: the threshold of the cumulative rotation angles
Output: *anomalyList* : A list records vehicles that have anomaly wandering round activity

```
for each vehicle Vi in vehicleList do
|     Traj= traceDict[Vi]
|     Partition Traj into a set of trips tripList
|     calculate RLF from tripList
|     calculate RRF using routeDict
|     if RRF≥TRRF and RLF≥TRLF
```

for each *path* **in** *tripList* do
calculate φ_{path} as fuction.5
if $\varphi_{path} \geq T_{\varphi}$
add V_i into *anomalyList*
end
end
end
end
return *anomalyList*

B. Temporal Anomaly Detection

In our temporal anomaly detection algorithm, named as distance from the centers of K-mean clustering (DCKC), there are two phases as well, i.e., clustering and outlier detection.

In the first phase, we select a set of vehicles with typical behaviors as the training dataset to compute the temporal feature vectors. The temporal features include *ADP* and *ASH*. Then we run K -mean [16] clustering algorithm on the feature vectors space to calculate K clusters, where each cluster represents a type of vehicles, such as buses and trucks. The centers of those K clusters are denoted as C=[$center_1$, $center_{2,...,}$ $center_k$].

In the second phase, the minimum distance from all centers was calculated for all vehicles in feature vectors space, where the distance is computed using Euclidean distance formula. The vehicles with minimum distance values exceeding a threshold T_d are selected as anomalies. The DCKC anomaly detection algorithm is shown in Algorithm 2.

Algorithm 2: Temporal anomaly detection based on distances from centroids of K-mean clustering (DCKC)
Input: *featureDict*: a hash table records all vehicles' temporal feature vectors (*ADP*, *ASH*);
vehicleList: a list records all vehicles' number-plate;
sampleList: a list records number-plate of vehicles chosen from typical training set;
T_D: the threshold of the route length factor
k: The number of clusters to form as well as the number of centroids to generate;
r: Number of iterations of the k-means algorithm to run
Output: *anomalyList*： A list records vehicles that have anomaly wandering round activity
new *array* object that is an array of feature vectors;
for each vehicle V_i **in** *sampleList* do:
(ADP, ASH)= featureDict [*i*]
array.append(*[ADP, ASH]*)
end
centerList, clusterIDList = kmeans (array, k, round) : *centerList* is a 'k' by 'N' array of centroids or geometric center found at the last iteration of k-means.
for each vehicle V_i *vehicleList* do
feature= featureDict [V_i]
for each *center* in *centerList* do
calculate distance *d* between *feature* and *center*
if $d \geqslant T_D$
add V_i into *anomalyList*
end
end
end
return *anomalyList*

IV. Experiment Evaluation

A. Dataset Collection and Parameters Setting

We have collected a dataset from the ANPR system deployed at the city of Wuxi between August 17, 2013 and October 24, 2013. This ANPR system has 314 cameras installed at 112 different gateways as show the red point in Fig. 3. The dataset used for experiments consists of ANPR records and corresponding front view pictures of vehicles. The total number of ANPR records is close to 114 million, which includes about 5.4 million vehicles.

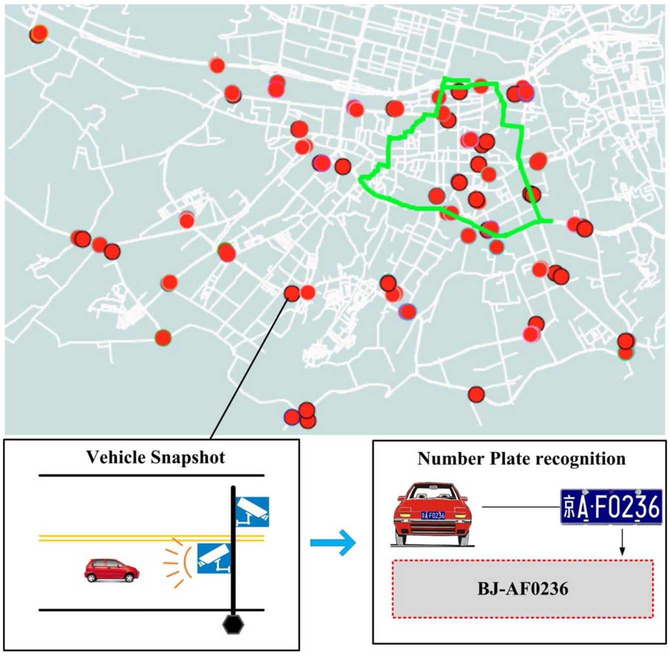

Fig. 3. Automatic Number-Plate Recognition System Deployment

We filter out noises in our collected data caused by inaccurate detection and recognition of license plates in this ANPR system. The filtering removes those records with unrecognized plate number and unrepresentative vehicles which have specific license plate numbers. The filtered dataset has over 490,000 different vehicles and about 4.9 million vehicles ANPR trajectory data records.

We tested the longest driving time between two deployed gateways is about 30 minutes at rush hours. It means that the ANPR record interval in one short-term trips should be no more than 30 minutes. Therefore, the *threshold* in trajectory partition phase is set to 30 minutes.

In CRAC based spatial anomaly detection algorithm, threshold T_{RRF} is set to 0.99, threshold T_{RLF} is set to 0.2. Threshold T_{φ} is set to 4π. According to our statistics results, there are more than 1.8 million different routes types. Over 90% routes have only one gateway and their length are 1. About 1% routes are of length longer than 20. Therefore, threshold T_{Lenth} in fuction.2 is set to 20. Threshold T_{Rarity} in fuction.3 is set to 100, which means that the *rarity* value would be 0 if there had more than 100 cars driving among that route.

In DCKC based temporal anomaly detection algorithm, threshold T_d is set to 0.5. The distribution of number of ANPR records at different hours shows that the vehicle activities have strong temporal patterns. Most vehicles (more than 90%) are active at mainly daytime. Therefore, we set the special period to be from midnight to 6:00AM. In our scheme, the number of iterations is set to 20.The set of vehicles features are divided into 5 clusters by K-means clustering methods with k=5.

We use simulation data to test the performance of our CRAC based spatial anomaly detection algorithm. In our simulation, five circular paths are generated based on the city's GIS map data. Each circular path has 6 gateways. The green line shown in Fig. 3 is one of the circular paths. The test vehicle has three turns in each circular path in simulation.

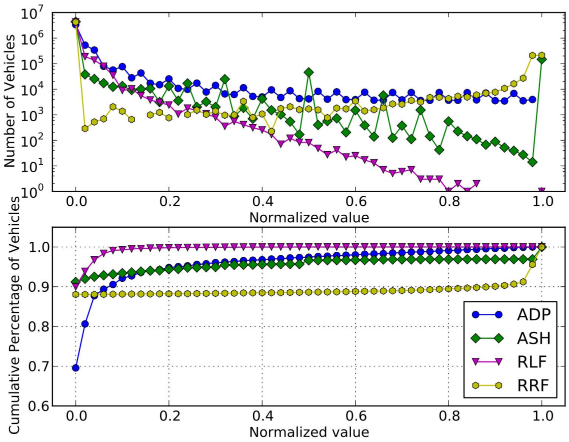

Fig. 4. Distribution of the vehicle numbers for the normalized values of trajectory features, value step is 0.02

The real world data is used to evaluate the performance of DCKC-based temporal anomaly detection algorithm. Here, selecting the training dataset affects the cluster centers, and consequently, affects the performance of this algorithm. Based on statistical results, we find that there are five common types of vehicles in dataset, including local family cars used to commute, forien cars used by tourists visiting the city, commute buses, passing-by commercial trucks, and local trucks. We manually label each vehicle to one of the five types according to the vehicle pictures captured by the ANPR system. Finally we randomly select 10,000 vehicles as our training dataset, 10% are commuter cars, 40% are cars used by tourists, 15% are buses, 15% are passing-by trucks, and 20% are local trucks.

B. *Performance of Anomaly Detection*

The distribution of the features values extracted from ANPR trajectories is shown in Fig. 4. About 70% vehicles' ADP values are close to 0, which means that these vehicles have showed up in only one day in our dataset. There are about 90% vehicles' ASH values are close to 0, which means that these vehicles had never driven in specific period. More than 98% vehicles' RLF values are less than 0.1, because the path lengths of these vehicles are no more than four gateways. More than 88% vehicles' RRF values are close to 0. That means the trips of these vehicles are common routes.

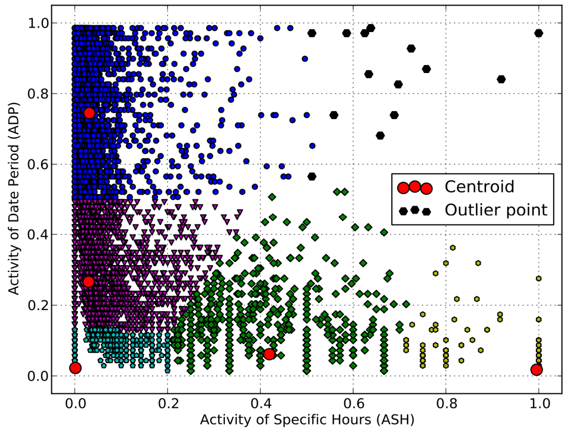

Fig. 5. DCKC temporal anomaly detection results

The result of DCKC based temporal anomaly detection algorithm is shown in Fig. 5. We use different colors of points to indicate the result of K-mean classification based on feature vectors (ADP, ASH) of the training dataset. The red points in Fig. 5 are the centers of each classification. The black points are the detected anomalies. The distances between black points and the centroids are always more than 0.5. Finally about 340 vehicles are determined as outliers.

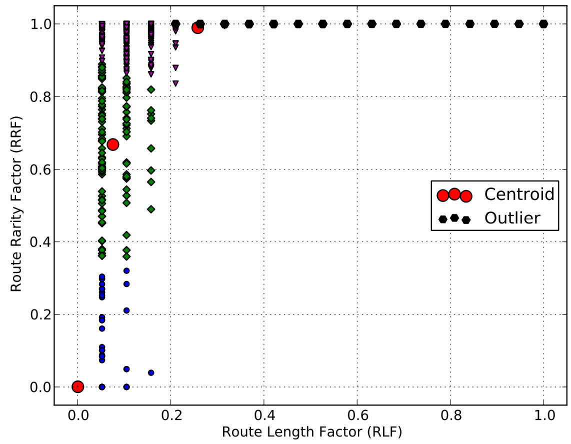

Fig. 6. CRAC spatial anomaly detection results;

The result of CRAC based spatial anomaly detection algorithm is shown in Fig. 6. The black hexagon points in Fig. 6 represent the detected vehicle anomalies whose RRF values have exceeded 0.99 and the RLF values are more than 0.2. After calculating the cumulative rotation angles around the centroid φ, there are about 120,000 anomaly vehicles and more than 1.5 million uncommon routes.

The number of detected anomalies is suspiciously large. We randomly choose some captured pictures of these vehicles for manual verification. We find that there are quite some numbers of illegal taxies active at the experiment area. These vehicles are wandering at small regions to carry passengers like taxi.

The ANPR cameras could not correctly recognize all of the license plates. The performance of our proposed anomaly detection algorithms is affected by the recognition probability of ANPR system. We also implemented the longest repeated subsequence based anomaly detection algorithm for comparison, and the lenth thresthold of longest repeated subsequence is set to 3.In Fig. 7, we show the detection rate of DCKC-based temporal anomaly detection algorithm and CRAC-based spatial anomaly detection algorithm under different recognitions probability of the ANPR system. Let *p* be the probability of a vehicles being captured and correctly recognized. We range probability p from 0.75 to 1.0 and generate 100,000 different datasets to run our simulation. The results are plotted in Fig. 7.

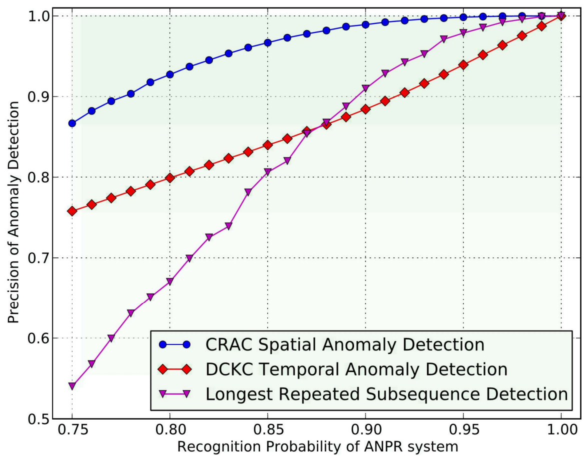

Fig. 7. Performance of proposed anomaly detection algorithm

As we can see from Fig. 7, the CRAC-based spatial anomaly detection algorithm is less affected by recognition probability of ANPR system. The DCKC-based temporal anomaly detection algorithm depends more on the recognition probability of ANPR system. The lower recognition probability will lead to unsatisfactory results of anomaly detection. And the longest repeated subsequence anomaly detection algorithm is greatly affected by the ecognition probability as shown in Fig. 7.

V. CONCLUSION

This paper proposes a new anomaly detection scheme that exploits vehicle trajectory data collected from ANPR system. Our scheme is capable of detecting vehicles with the behavior of wandering round and unusual activity at specific time. Our scheme first extracts trajectory feature vectors from the trip information recorded in ANPR records; then applies spatial anomaly detection based on cumulative rotation angles around the centroid (CRAC), and temporal anomaly detection based on distances from centers of K-mean clustering (DCKC). Some vehicle with its feature vectors is classified into anomaly vehicles. The performance of our anomaly detection scheme depends on the ANPR system's accuracy in recognizing the vehicle license plates. In our future work we will focus on processing the large number of unrecognized ANPR records, and investigate advanced pattern recognition techniques to recognize additional vehicle identity features, such as the logos and sizes.

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