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Video-based urban expressway traffic measurement and performance monitoring

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Abstract: This paper presents an urban expressway video surveillance and monitoring system for traffic flow measurement and abnormal performances detection. The proposed flow detection module collects traffic flow statistics in real time by leveraging multi-vehicle tracking information. Based on these online statistics, road operating situations can be easily obtained. Using spatiotemporal trajectories, vehicle motion paths are encoded by hidden Markov models. With path division and parameter matching, abnormal performance containing extra low or high speed driving, illegal stopping and turning are detected in real scenes. The traffic surveillance approach is implemented and evaluated on a DM642 DSP-based embedded platform. Experimental results demonstrate that the proposed system is feasible for the detection of vehicle speed, vehicle counts and road efficiency, and it is effective for the monitoring of the aforementioned anomalies with low computational costs.

Key words: multi-vehicle tracking; flow analysis, anomaly detection; behavior understanding; video surveillance and monitoring (VSAM)

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Currently, the urban expressway system of metropolises in China has taken shape. Urban expressways connect the main roads and the radial roads, gathering and distributing the traffic in central areas and connecting the urban and suburban areas. It plays an important role in the local transportation system[1-2]. Therefore, the surveillance system of urban expressways is of much importance for reducing traffic jams, ensuring the traffic service level and evaluating the transportation investment performance[3-4].

The key aspects of the urban expressway surveillance system are traffic measurement and performance monitoring. The traffic measurement system supplies real-time traffic data along with historical data by vehicle tracking. With these data, the performance monitoring system can detect anomalies or predict potential abnormal behaviors before they occur[5-6]. The basis of the surveillance system is road information acquisition. In Nanjing, large amounts of inductive loop sensors are in place. Inductive loop sensors deliver vehicle counts and lane occupancy from locations all over the city. Unfortunately, only half of the loop detectors supply usable data and they are costly to maintain. Cameras offer an attractive substitute for loops since they can be unobtrusively deployed on the side of urban expressways and can also be used for monitoring. In addition to providing traffic measurements, cameras can obtain more information such as travel time, vehicle classifications and irregular paths.

In this paper, we present a video-based automatic system which contains two different traffic situational awareness sub-systems. The first one is a traffic flow detection module for robust vehicle tracking and traffic statistical accumulation. The second one is the vehicle motion patterns learning module which is used to detect anomalies.

1 System Description

Generally, the distributed control system consists of three layers as shown in Fig. 1. Combined with the digital signal processing chip (DSP), the first layer is designed as an intelligent front-end processing unit which is called a video-based traffic flow measurement unit (VTFMU). The VTFMU performs traffic flow measurement and vehicle tracking. The second layer acts as the “node”, using the trajectory information up-transmitted by the first layer, to detect anomalous object motions. The third layer is the monitoring and managing center, which finishes city expressway incidents monitoring, emergency dispatch and optimal planning of road infrastructure. This paper focuses on the first and second layers to complete traffic flow acquisition and abnormal behavior monitoring.

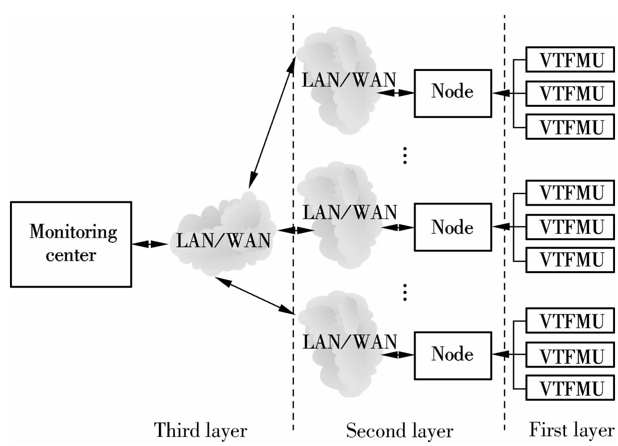

Fig. 1 Video-based distribution control system

2 VTFMU

The video-based traffic flow measurement unit selects the digital video and audio processor TMS320DM642, together with video codec chips to achieve the functionality. The unit works as a virtual sensor. Compared with the general sensor, the output of the virtual sensor is not simple numerical data such as analog or digital voltage, but road traffic infor-

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mation or the more advanced explanation. This portable device can be easily added in the existing video surveillance infrastructure on the roadside. The installation of the VTFMU in the surveillance system is shown in Fig. 2.

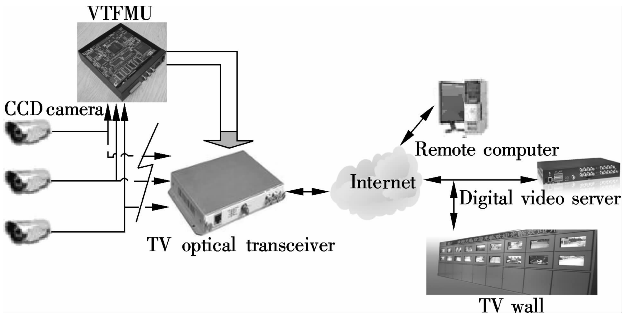

Fig. 2 Installation of VTMFU

2.1 Detection and tracking of multiple vehicles

Based on the DSP platform, we focus on real traffic scenes where there are many vehicles and mutual occlusions between multiple vehicles. Since the computational cost of most state-of-art detection and tracking algorithms does not scale linearly with the number of present objects, it is necessary to find a suitable algorithm with low computer costs. In this paper, a new spatiotemporal clustering-based tracking algorithm based on background subtraction and feature extraction is proposed to track multiple vehicles, which can resolve occlusion by using the temporal information carried by foreground pixels[7-9].

For fixed cameras, the background subtraction method is computationally efficient, and the key problem is to recover and update background images from a dynamic sequence[10]. In our algorithm, the background image is updated by the temporal average of an image sequence with an adaptation coefficient α.

$$B_{\text{updated}} = (1-\alpha)B_{\text{current}} + \alpha\pi_{\text{current}} \tag{1}$$

where B_{updated} is the estimated background. By computing the difference between corresponding pixels in the current image π_{current} and B_{updated}, foreground pixels in the current frame are identified.

The background subtraction method is adaptive to dynamic environments, but it generally does a poor job of extracting all the relevant pixels. There may be holes inside moving entities, so the foreground is further processed to fill in any holes using morphological operations[11-12]. We use the ratio of width to height to distinguish vehicles. After that, each blob is labeled by connected component analysis and the centroid of a vehicle blob can be described with a feature vector $\boldsymbol{f}$ containing its coordinates (x, y) and velocity (v_x, v_y). Compared with the coordinates, velocity is difficult to acquire. We use $(\delta x_i, \delta y_i)$ $(\delta x_i = x_i - x_{i-1}, \delta y_i = y_i - y_{i-1})$ to represent the velocity of the centroid at time i. The movement of vehicle n is represented by set Q_n, which is composed of t flow vectors $Q_n = \boldsymbol{f}_1, \boldsymbol{f}_2, \dots, \boldsymbol{f}_i, \boldsymbol{f}_{t-1}, \boldsymbol{f}_t$, where $\boldsymbol{f}_i = (x_i, y_i, \delta x_i, \delta y_i)$.

Tracking associates every detected vehicle with an existing track through nearest global matching. A prediction algorithm is used to produce the initial value for the corresponding centroid in the next frame. Usually, the Kalman filter is a good candidate for a prediction algorithm. In our work, many objects need to be tracked simultaneously, so there is a high computational cost. In order to decrease the computational cost, a fast prediction algorithm, the double exponential smoothing-based prediction algorithm, is selected. The running speed of the double exponential smoothing-based prediction algorithm is faster than that of the Kalman and the extended Kalman filter-based predictors[13-14].

Given a cluster centroid vector $\boldsymbol{f}_t$ at time t, its predictive value at time $t+\tau$ is calculated by

$$\boldsymbol{f}_t^{*} = \gamma\boldsymbol{f}_t + (1-\gamma)\boldsymbol{f}_{t-1}^{*} \tag{2}$$

$$\boldsymbol{f}_t^{**} = \gamma\boldsymbol{f}_t^{*} + (1-\gamma)\boldsymbol{f}_{t-1}^{**} \tag{3}$$

$$\boldsymbol{f}_{t+\tau} = \left[2 + \frac{\gamma\tau}{1-\gamma}\right]\boldsymbol{f}_t^{*} - \left[1 + \frac{\gamma\tau}{1-\gamma}\right]\boldsymbol{f}_{t-1}^{**} \tag{4}$$

where $\boldsymbol{f}_t^{*}$ smoothes the sequence $\boldsymbol{f}_t$ and $\boldsymbol{f}_t^{**}$ smoothes the sequence $\boldsymbol{f}_t^{*}$. The degree of exponential decay is determined by the parameter γ, $\gamma \in [0, 1)$.

2.2 Traffic flow analysis

The traffic measurement module cares about online flow analysis such as vehicle counts, driver's speed and link efficiency. Vehicle counts can be easily accomplished by the accumulation of new passing vehicles. It describes road congestion situations working with other measurements[15-16]. Driver's speed and link efficiency can be used as indicators of danger because it locates abnormal patterns based on online and historical data[17-18].

Speed is the estimated velocity of a tracked vehicle converted from the image distance to the actual distance by manual roadway calibration. By using a database of historical speed measurements, a model of daily speed patterns can be constructed to incorporate the traffic speed fluctuations. With the average daily speed, we define some special vehicles whose speed is abnormal as[13, 19]

$$S(v) = \begin{cases} \text{Stopped} & 0 \leqslant v < 0.15V_{\text{avg}}^t \\ \text{Slow} & 0.15V_{\text{avg}}^t \leqslant v < 0.6V_{\text{avg}}^t \\ \text{Normal} & 0.6V_{\text{avg}}^t \leqslant v < 1.1V_{\text{avg}}^t \\ \text{Speeding} & 1.1V_{\text{avg}}^t \leqslant v \end{cases} \tag{5}$$

where V_{avg}^t is the average speed at time t, and v is the estimated vehicle speed. By speed monitoring, first, the system can detect congestion and give the upstream section bypass warning; secondly, some incidents can be quickly detected from the "stopped" state which means traffic accident or violated behavior.

Some researchers use flow and speed to show that congestion is not caused by demand exceeding capacity but by inefficient road operation during periods of peak demand. Road efficiency at a given time t can be estimated[13] by taking into account the changes in flow, i. e.,

$$\hat{\eta}(t) = \frac{\text{flow}(t) \times \text{speed}(t)}{\text{flow}_{\max} \times \text{speed}_{\max}} \tag{6}$$

Nowadays several programs are used to improve the efficiency, such as the intelligent traffic signal control system and the bus priority system.

3 Performance Monitoring

Objects in the urban expressway scene do not always move randomly. Most of the time, they follow specific motion patterns. Knowledge of motion patterns can be used to detect anomalous object motions finished by the performance monitoring module. This module is an upgrade layer compared with a traffic measurement module. In urban expressway scenes, the unusual actions we focus on include violated vehicle U-turns, illegal parking on the roadside, extra fast or slow velocity of the vehicles and congestions. Based on this, a monitoring center can carry out traffic guidance to warn the drivers with variable traffic signs.

3.1 Pre-processing of trajectory

Before learning the paths, trajectories are filtered to remove tracking noise generated by incorrect tracking due to occlusion or overlap. So we manually define the entering or leaving regions corresponding to the true locations where vehicle tracking either begins or ends[20-22].

On the other hand, it should be noted that input trajectories must be normalized to the same length since trajectory length depends on the amount of time spent in the camera field of view, which varies from vehicle to vehicle. We use a linearity method to resample each trajectory to a fixed length L, i. e., $Q_n = \{\boldsymbol{f}_t\}_{t=1}^{L}$.

For two trajectories, we calculate the distance between the corresponding centroids in each frame. If all the consecutive points are within a small radius, i. e.,

$$d^t = \sqrt{(\boldsymbol{f}_i^t - \boldsymbol{f}_j^t)^{\mathrm{T}}(\boldsymbol{f}_i^t - \boldsymbol{f}_j^t)} < \varepsilon_{\mathrm{d}} \quad \forall\, t \tag{7}$$

or if the total distance between tracks is small enough, i. e.,

$$D = \sum_{t=1}^{L} d^t < \varepsilon_{\mathrm{d}} = L_{\varepsilon_{\mathrm{d}}} \tag{8}$$

two trajectories are merged. The merged trajectory is the mean of the centroid trajectories. The threshold should be chosen small enough to ensure that adjacent lanes are not merged (set ε_{d} to 5 pixels in our experiments), which is related to perspective projection foreshortening.

3.2 Probabilistic path modeling

Vehicle behavior in the urban expressway scene is relatively simple compared with the intersection scene. After paths merging, we can obtain a lesser scale of trajectories than those of all of the detected trajectories. However, we need to know not only where objects are located but also the manner in which they travel along a given path. Using HMMs, the spatiotemporal properties of every path are encoded[23], differentiating not only the locations but also the dynamics.

Each path is compactly represented as $\lambda_i = (\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{\pi})$ and is designed to have Q states ($Q_n = \{\boldsymbol{f}_t\}_{t=1}^{L}$). The parameters $\boldsymbol{A}$ and $\boldsymbol{\pi}$ can be manually defined by the inherent structure of paths

$$\pi_i = \mathrm{e}^{\alpha_{p^i}} \tag{9}$$

$$A_{ij} = \begin{cases} \mathrm{e}^{-\alpha_{\mathrm{b}}(I-j+1)} & j \leqslant i \\ \mathrm{e}^{-\alpha_{\mathrm{f}}(j-I+1)} & j > i \end{cases} \tag{10}$$

The rows of $\boldsymbol{\pi}$ and $\boldsymbol{A}$ are normalized to be valid probabilities. The transition rates $\alpha_{\mathrm{f}} \ll \alpha_{\mathrm{b}}$ are chosen for strong left-right tendencies. The only unknown parameter is the observation distribution $\boldsymbol{B}$, which is dependent on the model states $q_j|_{j=1}^{Q}$. The states are assumed to be Gaussian with unknown mean and covariance, i. e., $q_j - N(\mu_j \Sigma_j)$. Each HMM is completely specified after learning the states. The observations used to train the HMM path models incorporate the position and velocity $\boldsymbol{O} = \{x, y, \delta x, \delta y\}^{\mathrm{T}}$.

An HMM is trained for each route by dividing the training set into N_{p} disjoint sets, i. e., $D = \bigcup_{i=1}^{N_{\mathrm{p}}} D_i$. The set D_i is constructed by collecting all the trajectories classified into route r_i. Only those tracks that fit route r_i well are retained for training. The Q states from each of N_{p} HMMs can be efficiently learned using standard methods such as the Baum Welch method or EM. Finally, the set of original trajectories $\Gamma = T_1, \ldots, T_M$ is divided into K subsets:

$$\Gamma = \{\{T_{1,1}, \ldots, T_{1,M_1}\}, \ldots, \{\mathrm{T}_{i,1}, \ldots, T_{i,M_i}\}, \ldots, \{T_{K,1}, \ldots, T_{K,M_K}\}\} \tag{11}$$

where M_i denotes the number of original trajectories in the i-th subset[11].

3.3 Performance analysis

Given a trajectory, we calculate the probability of T under all the HMMs and look for the maximum likelihood path. The observations of trajectory T at time t is $\boldsymbol{o}_t = \{x_t, y_t, \delta x_t, \delta y_t\}^{\mathrm{T}}$. The path which best explains the given trajectory T is assigned as follows:

$$\lambda^* = \arg\max_i P(T \mid \lambda_i) \tag{12}$$

$P(T \mid \lambda_i)$ can be calculated by the forward-backward procedure which contains three steps. Consider the forward variable $\alpha_t(i)$ as

$$\alpha_t(i) = P(\boldsymbol{o}_1 \boldsymbol{o}_2 \boldsymbol{o}_3 \ldots \boldsymbol{o}_t,\ q_t = i \mid \lambda) \tag{13}$$

1) Initialization

$$\alpha_1(i) = \pi_i b_i(\boldsymbol{o}_1) \quad 1 \leqslant i \leqslant N \tag{14}$$

where $\boldsymbol{o}_1$ is the observation at time $t = 1$.

2) Induction

$$\alpha_{t+1}(j) = \Big[\sum_{i=1}^{N} \alpha_t(i)\, a_{ij}\Big] b_j(\boldsymbol{o}_{t+1}) \quad 1 \leqslant t \leqslant T-1, 1 \leqslant j \leqslant N \tag{15}$$

3) Termination

$$P(O \mid \lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{16}$$

So, every track is classified into a path. If the probability λ^* is less than a threshold T_{p}, the trajectory is treated as abnormal. The threshold can be determined during training by comparing the average likelihood of samples in the training set D_i with all those outside, i. e.,

$$T_{\mathrm{p}} = \beta(T_{\mathrm{in}} - T_{\mathrm{out}}) + T_{\mathrm{out}} \tag{17}$$

$$T_{\mathrm{in}} = \frac{1}{|D_i|} \sum_{k \in D_i} \log P(T_k \mid \lambda_i) \tag{18}$$

$$T_{\mathrm{out}} = \frac{1}{N_{\mathrm{T}} - |D_i|} \sum_{k \notin D_i} \log P(T_k \mid \lambda_i) \tag{19}$$

where the sensitivity factor $\beta \in [0, 1]$ controls the abnormality rate. Greater β values cause more trajectories to be considered anomalous by increasing the threshold.

4 Experimental Results

All the above algorithms are implemented using Visual C++6.0 on both the DSP platform[24] and the Windows platform. In the following, multi-vehicle tracking results are first introduced. Then, trajectory building is shown. Finally, the results of anomaly detection are demonstrated.

The multi-target tracking algorithm can resolve the target losing problem of dark color vehicles. Those vehicles of heavy blue and dark red look similar to the road in gray level shown in Fig. 3 and Fig. 4. The algorithm efficient to occlusion shown in Fig. 5.

In this part, we give the trajectory graph in different time intervals on the same road. Fig. 6 shows the learning results in which thick lines represent the mean of motion patterns.

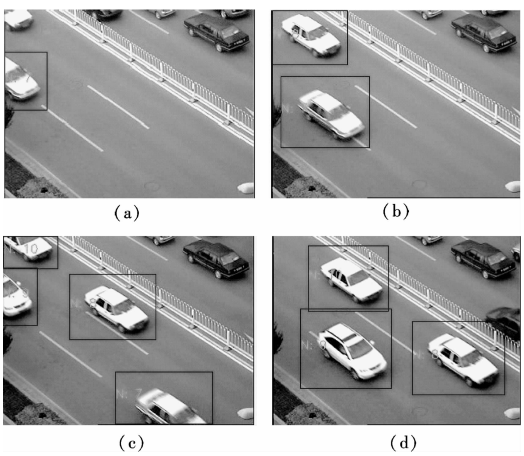

Fig. 3 Continuous tracking of white vehicles in different frames. (a) Frame 248; (b) Frame 265; (c) Frame 278; (d) Frame 291

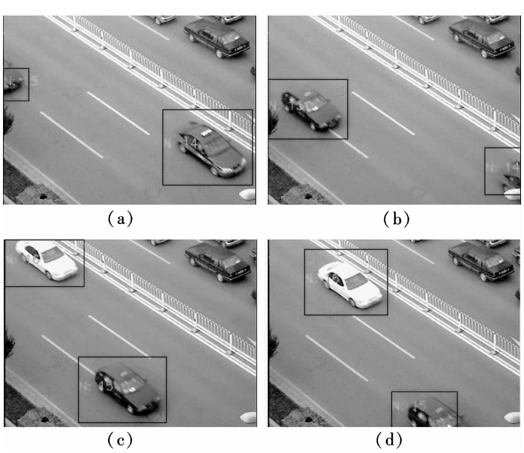

Fig. 4 Continuous tracking of dark vehicles in different frames. (a) Frame 429; (b) Frame 438; (c) Frame 447; (d) Frame 459

Fig. 5 Efficient tracking by occlusion

Fig. 6 Trajectories in different time

With the average daily speed, we outline some special vehicles whose speed is abnormal as shown in Fig. 7. Besides speed information, we can use trajectory analysis to detect abnormal speed. In Fig. 8, we capture an illegal U-turn action. However, anomalies do not always occur in real world scenes, so it is necessary to use the indoor model to test our anomaly detection approach.

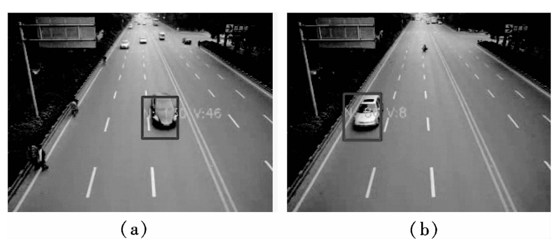

Fig. 7 Cars with abnormal speed. (a) Car with normal speed; (b) Car coming to stop on the roadside

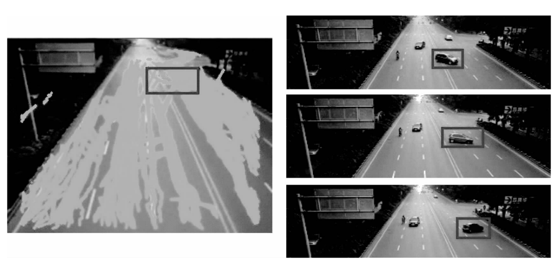

Fig. 8 Illegal U-turn

5 Conclusion

In this paper, a video-based surveillance system is developed for real-time urban expressway flow detection and performance monitoring. The traffic flow measurement unit solves the computational cost problem in real-time systems and is efficient in some occlusion situations. The present vehicle motion patterns learning module uses normal scene motions to build probabilistic models that encode the spatio-temporal nature of activities presented in the tracking data. Based on these statistical models, the proposed algorithm completes abnormal trajectory detection such as low speed driving, illegal stopping and turning in real scenes.

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基于视频的城市快速路交通流检测及车辆行为监控

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摘要:提出一种针对城市快速路的视频监控系统,完成交通流及道路异常行为检测.流量检测模块对车辆进行实时跟踪获得各类交通流统计数据,实现快速路车辆运行状况的全面掌控.异常监控模块运用隐马尔科夫模型,对带有时间和空间信息的车辆轨迹进行训练,获得路径划分后对道路车辆轨迹进行参数匹配,提取诸如超低(高)速行驶、违章停车、违规掉头等异常行为.所提监控算法在基于 DSP 的嵌入式 DM642 平台上得到应用和测试,试验结果表明:系统能够完成包括车速、车流量、道路利用率等信息的检测,并能对上述异常行为实施有效监控,算法运算量低、鲁棒性好.

关键词:多车辆跟踪;车流量分析;异常检测;行为理解;视频监控

中图分类号:U491