

## A Traffic Congestion Estimation Approach from Video Using Time-Spatial Imagery

Li Li, Long Chen, Xiaofei Huang, Jian Huang

*Joint Lab for Intelligent Computing and Intelligent Systems, School of Electronic Information  
Wuhan University, Wuhan, Hubei 430079, P.R. China*

*li@inass.org*

### Abstract

*This paper presents a novel approach to detect traffic congestion on roads in a natural open world scene observed from TV cameras placed on poles or buildings. In this system, a time-spatial imagery based algorithm is proposed to estimate the road status from the video. The experimental results on real road traffic congestion estimation show that the time-spatial method is robust in complex lighting and traffic environment. The detailed algorithm and the comparison results are given in the paper.*

### 1. Introduction

With the development of traffic infrastructure, many cities like Wuhan, China, installed hundreds surveillance CCD in urban area. Currently, these video always transfer to a monitoring center and analyze manually. The purpose of the work presented here was to provide video imagery based urban traffic monitoring methods to realize real-time traffic congestion estimation.

Traffic congestion in urban road and freeway networks leads to a strong degradation of the network infrastructure and accordingly reduced throughput, which can be countered via suitable control measures and strategies [1]. Most traffic information in ITS is based on ground sensors like induction loops, bridge sensors and stationary cameras. Sensor based system only used in few main roads due to high cost. Video based system used more wildly now, however, it's inefficiency in traffic congestion estimation. Thus because few video based methods were used in the system.

We made a survey of research work elsewhere, many works have been done on vehicle tracking applications that use image sequences, which mainly focused on vehicle classification and tracking [2-5]. In our system, the surveillance CCD camera is installed in

a relatively far distance from a highway and the vehicles are visualized as small objects with minimum detail on their geometrical model. The focus of our system is to estimate the road congestion situation rather than the detailed vehicle types and counts.

Normally the traffic situation can be roughly categorized into two states, open flow and congestion. However, these two categories are not enough to describe the traffic situation. Thus, in our system we proposed three traffic patterns; congestion (CG), Mild congestion (MC) and Open flow (OF) are defined. Congestion: there are a large number of vehicles and almost all of the vehicles run very slowly or completely stopped. Mild congestion: there are a large number of vehicles and most vehicles run slowly. Open flow: vehicles run at normal speed. According to this definition, two parameters can be used to determine the road situation: the occupation rate of the vehicles on the road and the status of the movement of the vehicles. In the Open flow situation, the occupation rate of the vehicles on the road is low and the vehicles are moving at normal speed; in the mild congestion situation, the occupation rate of the vehicles is relatively high and the movement is slow; in congestion situation, there's hardly any movement and the occupation rate is very high. So our task can be categorized into two tasks:

- Detect the movement status of the vehicle.
- Compute the road occupation rate of the vehicle.

Several ways are tried to detect the movement status of the vehicle and road occupation rate. Such as background subtraction based method and frame differencing based method.

Background subtraction is a very popular approach because it's easy to implement, but in some cases like heavy congestion and abrupt change in light, it's hard to get a satisfying background model.

Frame differencing based method has relatively steady performance against environmental changes. However when the camera places very high and the

vehicles seem very small in the video, the results is unsatisfying.

Traffic congestion situation in a certain site reflects the relationship of moving objects – vehicles between temporal and spatial. Based on this principle we proposal time-spatial image based method for congestion estimation. The most similar thing that we found was the work by Antonio Albiol et al. [6] for people counting. They built space–time images and use morphological tools for detection. The concept is the same, but the objective and environment are difference. They focus on objet segmentation and isolation, in our case object situation is the most important information. However they do not seem to have the problem of objects stagnation.

Recently, A. Liu et al. [7] and J. Wu et al. [8] proposed methods based on virtual line for vehicle detection. Their approach has some similarities with ours – they use video base image and detect vehicle. There are however many differences between their work and ours; they use background information and virtual line for vehicle detection optimize, while we not use background but get pattern characters from the generated time-spatial image. The environment shown in their examples is in freeway and daylight condition, while our case is more complex in urban area and intercourse.

To be an effective traffic surveillance tool, a video image processing system should meet several stringent requirements [9]:

- Function under a wide range of traffic conditions: light traffic, congestion, varying speeds in different lanes.
- Function under a wide variety of lighting conditions: sunny, overcast, twilight, night, rainy, etc.
- Operate in real-time.

In our system, we first raised time-spatial image methods for traffic congestion estimation and used different methods in complex environment. The algorithm meets the requirement and demonstrates good results. The time-spatial method is robust in complex lighting and traffic environment.

The rest part of the paper is organized as follows. In section 2 describes the proposed methods and algorithms. Section 3 presents comparison experimental results and Section 4 concludes this paper.

## 2. Time-Spatial image based method

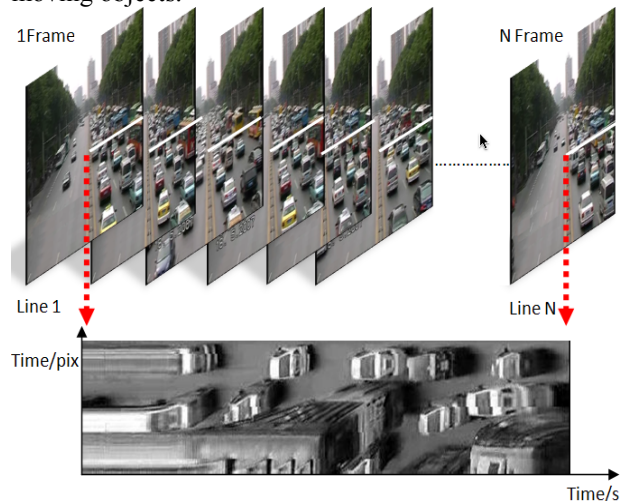
### 2.1. Generation of Time-spatial image

In two dimension video image, the relationship between moving objects and static background isn't easy to find. Since a vehicle usually takes more than one frame to cross a *virtual detection line* on the road, some time memory must be included in the algorithm [6].

We acquire a new frame to store certain lines of the frame onto what we have called *Time-spatial image*. These stacks of lines contain all the required information to detect vehicle status, and can be considered itself as an image.

Time-spatial image merges the characteristic both of temporal series and spatial sequence. It's good for reflecting differences of moving vehicles and static objects. In time-spatial image, image spreads in space and time coordinate as Fig.1.(a). Such images can be perceived as detector staring-map by line detector. We could say that stacking act like an information condenser, passing from a sequence from Time-spatial image slice. Different rows are reflected in the corresponding detection line in time. In the paper a white line selected as line detector, see white lines in each frame of Fig.1.(a)., and in chronological order from left to right these detection lines generated time-spatial images Fig.1.(b).

Under this generation method, time-spatial images reflect the image of a fixed region (line) changes with time. If no objects moving in detect region, there is no gray changed. Otherwise, gray will be changed by moving objects.



**Fig.1. The Generation Procedure of Time-Spatial Image.**

In certain sample frequency, the faster the movement objects, the shorter it stayed in the region; the contrary is longer. In the image, the length of gray changes  $t$  is inversely proportional to object velocity  $v$ . After normalized, it's according to following equation:

$$v=1/t \quad (1)$$

When objects is static, the length  $t$  (x axis) is infinite; when speed is not zero, the length  $t$  is limited, with Eq.(1)

In time-spatial image, horizontal axis is the time line shows vehicle time information, while the vertical one is space-axis shows vehicle space information. The image height equal to the detection line (white line) length; and the image width ( $t$ ) can be calculated as:

$$t=N/a \quad (2)$$

$N$  is the number of frames, and  $a$  is the frame rate per second. In the paper  $N=100$ ,  $a=15$ , thus  $t=6.67s$ .

## 2.2. Collection rule of Time-spatial image

To ensure traffic congestion estimate accuracy, a set of rules are proposed in detection line setting and time-spatial image generation. These rules are listed as follows:

**Rule1:** set the line perpendicular to the direction of cars travelling and near intersection of roads;

**Rule2:** span of the line includes vehicles' projection area on the road;

**Rule3:** width fix to 1pixex; length longer than 2 lanes width in the same direction, no less 50 pixels;

**Rule4:** frame number no less than 100 to get enough information and no more than 150 to ensure real-timing.

Fig.2 gives the time-spatial images of all kinds traffic situation in scene 1.

## 2.3. Relationship of Time-spatial image and CG

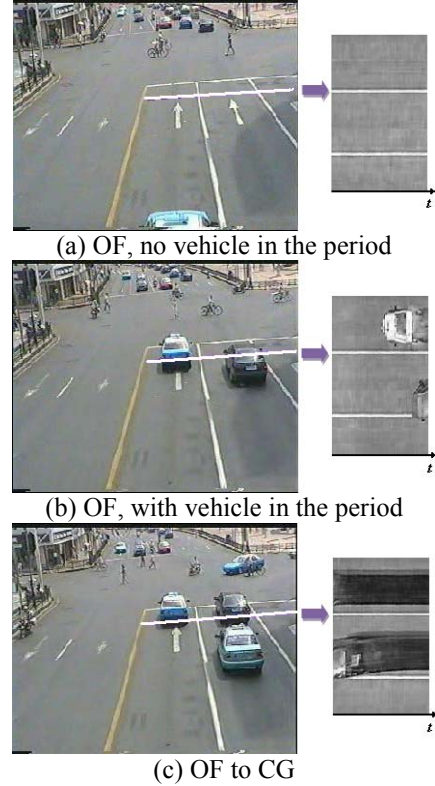
From time-spatial images, it can directly reflect the state of road congestion and trends. When vehicle speed faster, image block length is shorter and area is smaller; when speed slower, the length is longer and area also will be increases; when road congestion, the images show many straight lines or horizontal stripes. The obvious characteristics can be detected with Hough transform, Fig.3 shows typical situation of OF and CG.

We use Canny Edge Detector to detect edges [13]. Then use Hough transform to detect edge stripes or lines. Then calculate the length  $L$ , direction  $D$  and line number. Filter the lines with these parameters, and get valid horizontal line number  $N$ . The edge occupation rate  $r$  can be calculated as 2.2 described, compare  $r$  with threshold  $T_r$  and  $N$  with  $T_N$ . If both of them greater than given threshold, it belongs to congestion status, otherwise road is over flow. This can be defined by:

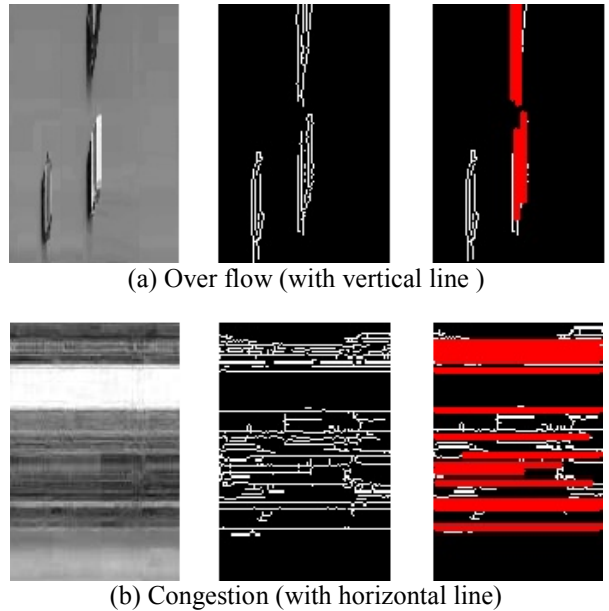
$$CG: \{ N > T_N \text{ And } r > T_r, \text{ And } L > T_L \} \quad (3)$$

$$MC: \{ N > T_N, \text{ And } r > T_r, \text{ And } L < T_L \} \quad (4)$$

$$OF: \{ \text{otherwise} \} \quad (5)$$



**Fig.2. Time-spatial images examples under different traffic conditions**



**Fig.3. Time-spatial image congestion analysis**

## 2.4 Congestion estimation by Time-spatial Image

After learning congestion estimation strategy by image like Fig.3, the time-spatial image can be used to detect congestion by Hough transform and edge detection as following steps:

**Step1:** Image preprocessing, change color frame to grey;

**Step2:** Setting detection line as rule1-4. In our work line can be set in any direction, thus can meet different layout of intercourse and lanes;

**Step3:** Generate Time-spatial image;

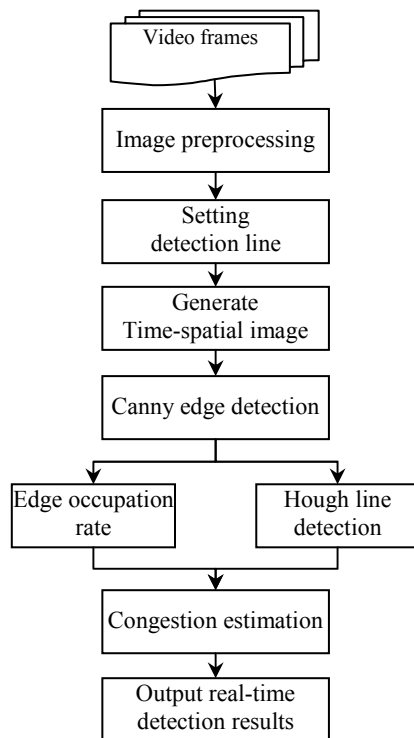
**Step4:** Use Canny Edge Detector to detect edges as 2.2.descripted.

**Step5:** Use Hough-transform to detect line pattern. Then calculate the length  $L$ , direction and line number. Filter the lines with these parameters, and get valid horizontal line number  $N$ .

**Step6:** Calculate the edge occupation rate  $r$ ;

**Step7:** Congestion estimation according to eq.(3-5)

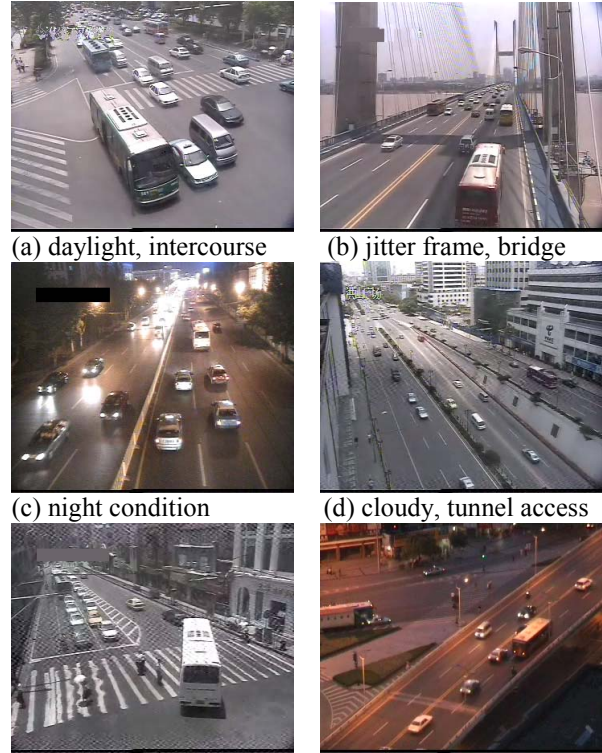
Fig.4 shows the flowchart of the time-spatial image detection algorithm.



**Fig.4. Flow chat for time-spatial image base method.**

## 3. Experimental results

The proposed method is evaluated on real video clips which covered more than 20 roads and intersection in Wuhan City of China. These video are collected in various traffic and light conditions: night, evenfall and daytime. In some of the video, the camera is placed on the viaduct and jitters seriously. Each site includes OF, CG and MC clips. Fig.5 shows different clips for congestion estimation.



**Fig.5. Different Testing Environment**

Original video frames are color image, with size of 352\*288 (CIF/PAL), and frame rate of 15FPS. Each frame is converted to eight bits gray scale in image preprocessing procedure.

From Table 1, 20 sites materials divided into two groups according to corresponding situation. Each column gives statistic results under different methods. It can be seen the detection rate of proposed methods are from 92.7% to 95.3%. The detection rates vary with the complexity of road traffic and environment situation. Generally, the average detection rates in daylight are greater than that of night and jitter situation. Time-spatial imagery based approach shows very robust in different situation.

The false estimation results are mainly due to low contrast image, small vehicle block and irregular lane direction, etc. In normal condition our experimental results showed high accuracy compared with manual results.



**Table 1. Detection rate comparison results of three methods**

	Situation	Manually		time-spatial image based method	
		#OF	#CG	#OF	#CG
1	daylight	13	7	12	7
2	daylight	15	11	14	10
3	daylight	12	9	12	8
4	daylight	13	7	12	6
5	daylight	14	6	13	6
6	daylight	20	5	19	5
7	daylight	17	6	16	5
8	daylight	11	9	11	9
9	daylight	15	8	15	8
10	daylight	19	6	18	6
11	jitter	13	10	12	9
12	jitter	16	9	15	8
13	jitter	13	7	12	7
14	jitter	17	7	15	7
15	jitter	15	5	14	5
16	jitter	14	11	14	10
17	night	20	15	19	14
18	night	22	13	20	12
19	night	27	8	24	7
20	night	30	5	29	5
TOTAL		336	164	316	154
Detection rate (daylight)				95.3%	94.6%
Detection rate (jitter)				93.2%	93.9%
Detection rate (night)				92.9%	92.7%
Detection rate (Average)				94.0%	93.9%

#### 4. Conclusions

This paper presents a traffic congestion estimating approaches that is designed to operate under challenging conditions like lighting transitions between night/day and day/night, camera vibration due to wind etc.

The concept of Time-spatial image was introduced in our approach, and algorithm was given for traffic congestion estimation. The experimental results on real road traffic congestion estimation show that our approach has good congestion estimation performance.

Future work would mainly setup congestion estimation model in disadvantageous situation.

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