Electronic Traffic Jam Detection in Parking Facilities

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Abstract. This paper explores the possibility of traffic jam control and detection systems modelling. The traffic jam detection model was developed. This paper proposes jam forecasting and detection method using the neural network and fast Fourier transform. In this method, time series data of traffic flow events considered as a combination of frequency are transformed into several frequency data.

Keywords. Traffic jam measure and security, automatic detection and handling system of parking vehicles, intelligent transport systems.

1. Introduction

Big vehicle concentrations can cause traffic jams in the parking area and in the areas near these objects. This rising traffic flow can cause: rise exhaust gases in the parking area, bigger possibility of accidents such as fires, terror acts and others. In these areas usually not only cars but also peoples are constantly visiting, so if we have big vehicle concentration in one place (especially in the closed, or multi floor parking areas) we have to take care of area air ventilation, lighting, heating and others[1].

One of the ways to help to solve these problems is electronic control systems. To help solve these problems we can use many different electronic control subsystems.

One of the most important parking control system target is to detect and control possible traffic jams. Parking control systems part is traffic jams recognition and control systems. Few types of traffic jams in the parking-lots can be described: traffic jams on entry/exit roads, on raise and down ramps and on roads to parking lines. Best way to avoid such a jams is to detect not only traffic jam which is already formed, but to detect raised possibility of forming traffic jam. If we can detect the raised possibility of traffic jam formation we can take actions to avoid this traffic jam by: closing some entries exit roads, parking areas, inform drivers to avoid some suspicious places and in this way avoid traffic jams[2,3].

2. Traffic Jams Detection Using Neural Network

The standard procedure for use of a neural network involves "training" the network with a large sample of representative data. To find such a phenomenon appearing before traffic jam is formed in the parking facility 12 inductive road loops was installed. Inductive road loops are installed on the entry/exit roads and near each rise and down ramps. Automated measurements and registration system was created to collect traffic flow data, see this system structure in the Fig. 1.
Two main parameters were registering during this experiment: time between cars passing inductive road loop and time of cars passing inductive road loop (cars speed). To recognize and forecast traffic jams in the parking-lot model with neural network using Levenberg-Marquardt optimization [4,5] was done. For the modelling Matlab nftool library was used.

Structure of neural network is shown in the figure 2. For training and testing this neural model 510 data sets was prepared.

Each data set includes events of times between incoming cars and times of car passing inductive road loop [6]. Half of the data sets represent events which are occurring before traffic jam is formed and half data sets represent simple events when no traffic jam is formed. Output data set was also prepared.

During modelling was tested how many data sets neural network needs to recognize and forecast traffic jam. In figure 3 we can see mean square error pivot to the data sets quantity. And in the figure 4 regression (correlation) coefficient pivot to the data sets quantity we can see.

Figure 2. Structure of neural network

Analyzing the results we see that with neural network we have maximum reached successful traffic jam forecast with probability $p=0.82$. Also to reach forecasting probability $p=0.82$ we need minimum 8 events and it is enough 400 data sets to train this network. As it is very important to recognize traffic jam before it is formed so modelling showed that we can forecast it before approximately 5-10 seconds before it is formed.

Another way to detect and forecast traffic jams events is usage fast Fourier transform (FFT).
3. Traffic Jams Detection Using FFT

In this method, time series data of traffic flow events considered as a combination of frequency are transformed into several frequency data [7]. Figures 7 and 8 illustrate graphs of receivable signals spectrum and distribution from inductive loops. As we see in figures 7 and 8, when there are different transport flow during different period of time, the inductive loop signals spectrum $S(f)$ and distribution $P_k(t_k)$ differs. In order to compare these spectrums and distributions, at first we have to approximate these FFT results using exponential function.

$$S(f) \text{ Small flow} \quad S(f) \text{ Medium flow} \quad S(f) \text{ Big flow}$$

$$5 \times 10^{-5} \quad 5 \times 10^{-5} \quad 0.0005 \quad 0.0050 \quad 0.0500$$

$$f, \text{ Hz}$$

Figure 7. Traffic flow signal spectrum

$$P_k(T_k) \text{ Small flow} \quad P_k(T_k) \text{ Medium flow} \quad P_k(T_k) \text{ Big flow}$$

$$9 \quad 10 \quad 20 \quad 30 \quad 40 \quad 50 \quad 60 \quad 70 \quad 80 \quad 90 \quad 100$$

Figure 8. Traffic flow distribution in time scale

As we see in the figure 9 the major difference of inductive road loop FFT signal spectrums is seen in frequency range $f = 10^{-5} + 10^{-3}$ Hz.

Figures 9-10 illustrates three separate occasions signal spectrums and distribution approximated with exponential function results. The spectrum approximated functions show an evident distinction between separate transport occasions. We see in this example, that using this function, we can evaluate existing transport traffic from these functions parameters.

$$S(f) \text{ Small flow} \quad S(f) \text{ Medium flow} \quad S(f) \text{ Big flow}$$

Figure 9. Traffic flow signal spectrum approximation with exponential function

$$P_k(T_k) \text{ Small flow} \quad P_k(T_k) \text{ Medium flow} \quad P_k(T_k) \text{ Big flow}$$

Figure 10. Traffic flow signal distribution approximation with exponential function

We can also analyze with the same method and the inductive loop actuation time (time, when a car goes through the loop – the speed of the car) signals. The accomplished graphs of receivable signals spectrum and distribution is shown in the figures 11 and 12.

$$S(f) \text{ Small flow} \quad S(f) \text{ Medium flow} \quad S(f) \text{ Big flow}$$

Figure 11. Loop actuation spectrum and approximation with exponential function
The spectrum approximated functions show an evident distinction between separate traffic occasions.

![Figure 12. Loop actuation distribution and approximation with exponential function](image)

Figure 12. Loop actuation distribution and approximation with exponential function

It is very important to evaluate, how the transport traffic is influenced, when it is measured in the other point after particular distance or after a road fork in the parking area, see figure 13.

![Figure 13. Inductive loop location scheme](image)

Figure 13. Inductive loop location scheme

Figure 14 illustrates two inductive road loops IK4 and IK8 signal spectrums. Figure 15 illustrates the same loops signal spectrums, when there is low transport traffic.

Figures 16 and 17 illustrate the loops signal distributions.

Analyzing the inductive road loops IK4 and IK8 signal spectrums correlate with each other, in the parking area road loops existing away several hundred meters from each other and between them existing some turning off from parking lanes are very strong related, and using the information about further existing loops we can forecast about next loop traffic information.

All occasions when the transport traffic is big or low, two loops, which are in the same parking facility entrance road with turns to the parking lanes interacting remote, signals correlate with each other. Thus, we can see, that using road loops signal we can forecast transport traffic in next road loops entrance roads.
It has been accomplished parallel experiment in departure roads. In this occasion the distance is about 80 meters between loops IK1 and IK7 and 4 departures from parking lanes. Thus, it can appear more departing car turning off from parking lanes.

Figure 19 illustrates two inductive departure road loops IK3 and IK5 signal spectrums. Figure 20 illustrates the same loops signal spectrums, when there is low traffic flow. Figures 21 and 22 illustrate loops signal distributions. Assembled information from eight loops, we accomplished fast Fourier transformation of these loops signals and we analysed if these two loops signals correlate with each other. The analysis was accomplished in seven specific days, it is on 10th April, 2007, on 11th April, 2007, when the shopping mall was open and there were very big transport flow and traffic jams, on 14th April, 2007, on 15th April, 2007, when there were average transport traffics and traffic jams are very rarely and on 23rd April, 2007, on 24th April, 2007, on 25th April, 2007, workdays, when attendance is very low in the shopping mall and there were no traffic jams in parking facility.

Analyzing inductive road loops IK3 and IK5 signal spectrums correlate with each other, in the parking area inductive loops existing away several hundred meters from each other and between them existing some turns from to parking lane are very strong related, and using the information about further existing loops we can forecast about the neighbouring points of transport traffic in departure roads.

As we see in all occasions when the transport traffic is big or low, two loops, which are in the same departure road of parking area with entrance from the parking lanes interacting
remote, signals correlate with each other. Thus, we can affirm, that using the road loops signal we can forecast about traffic flow in next road loops.

It has been accomplished a parallel experiment in the departure road, where the distance is about 300 meters between loops and 11 turns off from parking lanes. Thus, it can appear a lot of departing cars turning off from parking lanes in the departure road and it strongly influent to the traffic flow.

As we see from figures 22-25, these traffic flow spectrum and distributions are different.

4. Conclusions

Traffic jam forecasting and detection method using the neural network allows us recognize traffic jam before it is formed. Modelling shows that we can forecast it before approximately 5-10 seconds before it is appears.

Analyzing inductive road loops signal spectrums correlate with each other. Inductive loops existing away several hundred meters from each other and between them existing some turns off from to parking lane are very strong related, and using the information about further existing loops we can forecast about the neighbouring points of transport traffic in departure roads.

We can affirm, that the further the road loops are from each other and the more there are entrance/turning off in/out parking lanes in that space, the more transport traffic spectrums and distributions vary. Thus, if there is a particular distance between separate controllable road parts of parking facility, using the information about the next loop we can forecast situation and on that ground optimize the management of transport traffic flow.

5. References


