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# THE GRANULAR COMPUTING IMPLEMENTATION FOR ROAD TRAFFIC VIDEO-DETECTOR SAMPLING RATE FINDING

**Summary.** The method discussed in this contribution allows to estimate the necessary data granularity for an on-line traffic controlling, using the information recorded by digital video-camera. Due to define the data sampling rate modelling and analysis methods were applied. They are used for extracting prediction rules of the traffic descriptors. The discussed scheme combines granular computing algorithms with assumptions of a cellular automata traffic model. It enables direct determination of temporal characteristics for the recognised and extracted traffic states. The traffic parameters prediction algorithm was introduced that allow determining the sampling time intervals of the video detection system.

# ZASTOSOWANIE TEORII OBLICZEŃ ZIARNISTYCH DO WYZNACZANIA CZASU PRÓBKOWANIA WIDEO-DETEKTORA POJAZDÓW

**Streszczenie.** Metoda przedstawiona w niniejszym artykule pozwala na oszacowanie poziomu ziarnistości danych niezbędnego do sterowania on-line ruchem drogowym na podstawie informacji obrazowej rejestrowanej kamerą wideo. W celu zdefiniowania czasu próbkowania danych zastosowano metody modelowania i analizy, które pozwalają na wydobycie reguł predykcji dla deskryptorów ruchu drogowego. Prezentowana metoda stanowi połączenie algorytmów granulacji danych z założeniami komórkowego modelu ruchu. Metoda ta umożliwia bezpośrednie określenie charakterystyk czasowych na podstawie rozpoznanych stanów ruchu pojazdów. Zaproponowano algorytm predykcji parametrów ruchu drogowego, który pozwala wyznaczyć przedziały czasu próbkowania dla systemu wideo-detekcji.

## 1. INTRODUCTION

The granular computing is known in many general computation theories using granules (classes, clusters, subsets, groups and intervals) for sufficient computing models finding. The big amount of data [1] can be remarkable reduced for well defined time relations of the controlling processes. The data granules define complex entities used for problem solving and modelling on different levels of resolution. Numerous works have dealt with the granular computing approach for data mining that aims at discovering knowledge embedded in the data [1, 4, 9, 10].

In this paper the implementation of the granular computing, for road traffic data analysis was discussed. Video processing methods used for vehicles detection in a road traffic measuring provide us with enormous amount of data. The registered traffic has to be analysed on-line, in a time period defined by functions of a controlling systems. This aim can be achieved by methods based on granular computing that was applied for reducing the sampling rate of a discreet data collecting unit. Sampling rate is defined as a time interval between successive executions of video processing procedure for traffic events detections.

The traffic parameters prediction method was proposed and applied in the traffic events video detection system for sampling rate selection. The discussed method applies granules of traffic data for the prediction rules induction. Granulation procedure includes video detection results registration using cellular traffic model. Registered data is used to compute statistics that are needed for prediction rules determination.

The paper explains some works of the author at the research project of video-detectors implementation in the traffic analysis and control systems. Section 2 presents basic assumptions and steps of the sampling rate finding algorithm for video detection systems. In section 3 the discussion of data granulation method for a road traffic model is presented. The sampling rate computation method, using data granules is presented in section 4. Some experimental results of sampling rate finding for vehicles queue video detection system are shown in section 5.

## 2. THE SAMPLING RATE FINDING ALGORITHM

The traffic control systems need to respond to specified events e. g. presence of an incoming vehicle in detection area or discharging of vehicles queue. The response of traffic control system has to be as quick as possible. Thus, it is necessary to detect such events immediately after their occurrence.

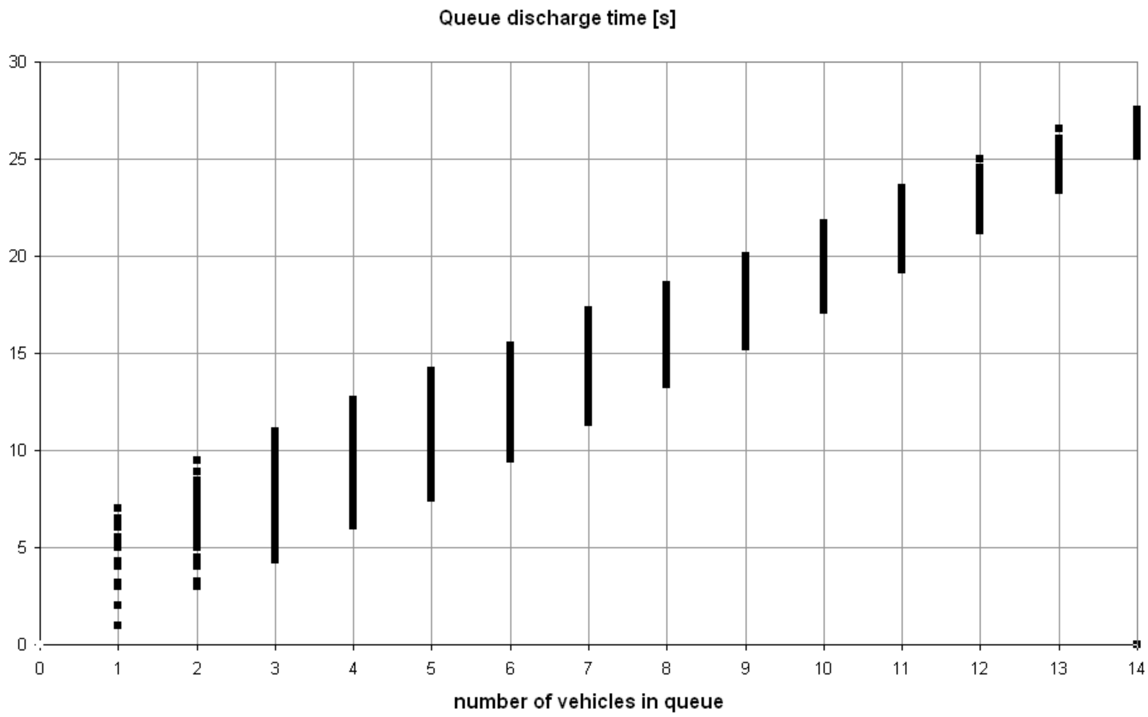


Fig. 1. Results of traffic simulation: vehicles queue discharge time
Rys. 1. Wyniki symulacji: czas rozładowania kolejki pojazdów

To perform the detection task defined above, without additional assumptions, detection unit should identify the traffic state with maximal sampling rate. However, using the historical data, it is possible to predict the time, when selected event can occur. It means that one can determine the time interval, for which the probability of event occurrence is close to zero.

For example if there is a long queue of vehicles in a crossroad inlet, a considerable time is needed for this queue discharging (Fig. 1). That is why we can assume that the queue will exist for a defined time period and in this interval the queue discharging need not to be detected. This way the sampling rate of the detection system significantly can be reduced.

Results of traffic simulation presented in Fig. 1 describe time values of vehicles queue discharging process for an exemplary crossroad approach. The NaSch cellular traffic model [6] was used in this simulation process.

Number of vehicles in the queue was modelled as a number of occupied cells in the cellular traffic model consisting of 14 cells. Queue discharge simulation was performed for all possible configurations of the cells.

Results of this experiment shows that the sampling rate for queue video detection can be considerably reduced, especially when the number of vehicles in the queue is large. For example, if 7 vehicles are waiting in the queue, the sampling rate can be set to 10 seconds. This assumption is based on the experimental results, showing that registered queue cannot be discharged in time shorter than 10 seconds. In the proposed inferring method the experimental results obtained by simulation are replaced by historical traffic data, registered in form of granules.

The introduced algorithm of sampling rate finding for video detector includes the following steps:

1. Traffic data granulation using cellular model.
2. Statistics computation for traffic parameters prediction on the base of registered data.
3. Induction of the prediction rules that define sampling rate for video detection system.

The operations listed above are discussed in details in the following sections. The result of presented algorithm is a set of rules that determine sampling rate for video detection as a function of current traffic state.

This algorithm can be used for traffic events detection of different kinds. In this contribution some results are presented of sampling rate finding for vehicles queue detection system.

## 3. THE TRAFFIC DATA GRANULATION

The traffic control systems need to respond to specified events e. g. presence of an incoming vehicle in detection area or discharging of vehicles queue. The response of traffic control system has to be as quick as possible. Thus, it is necessary to detect such events immediately after their occurrence.

The main aim of a road traffic modelling is to describe spatiotemporal characteristics of the vehicles movement. Traffic parameters are usually evaluated for a given road segment and time interval. Thus, definitions of space (road) and time granulation are necessary for data analysis using traffic models. Straightforward identification of data granules in a traffic model enables implementation of the granular computing methods for traffic parameters computations.

In many cases the data granules can be easily identified, especially for the discrete traffic models [4], where cellular traffic models plays an important role. The cellular models assume traffic lanes division into segments called cells. The cell size is different for different models; microscopic models use cells that can be occupied by a single vehicle [6] and in macroscopic models one cell is dedicated for a group of vehicles [3], [5].

The cell may be considered as a data granule in the description of a road traffic stream. In the presented study a space granulation based on the cellular traffic model was proposed. Furthermore, zooming-out and zooming-in operators were defined for the proposed granulation. Zooming-out operator deals with the shift from a fine granularity to a coarse granularity. This operator discards certain details, which makes distinct road cells no longer differentiable. The zooming-in operator defines the change from a coarse granularity to a fine granularity, providing more details in traffic stream description.

The introduced granulation involves dividing the traffic lane into cells. The granule describes the segment of the traffic lane (called cell) characterised by its state.

The state of the cell defines as a value of traffic density (number of vehicles present in the cell). Thus, granulation is a set of cells $\{i\}$ and configuration is a set describing current states of the cells $C_L = \{c_{1,L}, c_{2,L}, ..., c_{n(L),L}\}$, where $L$ denotes level of granularity, $c_{i,L}$ is a state of cell number $i$ for granularity level $L$ and $n(L)$ is a number of cells at granularity level $L$.

At the lowest granularity level ($L$ = 1) states of the cells have binary values: $c_{i,1} = 0$, if the cell $i$ is empty and $c_{i,1} = 1$, if there is a vehicle present in the cell $i$. Accordingly, at higher granularity levels ($L$ > 1) the state values of a cell denote number of vehicles present in the cell: $c_{i,L} \in \{0,1,...,L\}$.

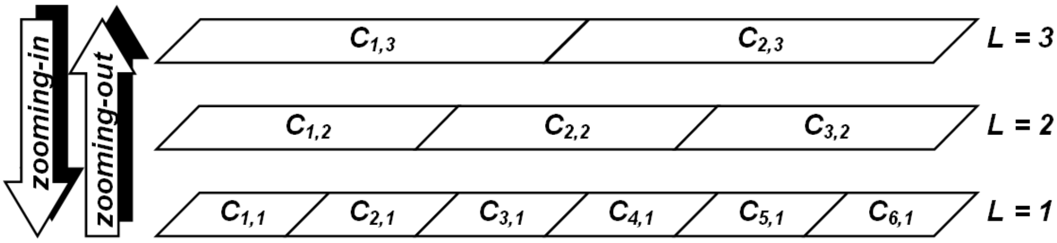


Fig. 2. Traffic lane granulation
Rys. 2. Granulacja pasa ruchu

By zooming-out operation, a subset of the cells is considered as a whole. This causes that information is lost. The zooming-out for traffic lane granulation is a mapping $C_1 \rightarrow C_L$ defined by formula:

$$c_{j,L} = \sum_{i=jL-(L-1)}^{jL} c_{i,1}, \quad j = 1,...,n(L), \quad n(L) = n(1)/L\,. \tag{1}$$

For granularity levels $L$ and $2L$ the following equality is true:

$$c_{j,2L} = c_{2j-1,L} + c_{2j,L}\,. \tag{2}$$

Zooming in is a multi-valued mapping: $C_L \rightarrow \{C_1\}$. By the zooming-in operation on a cells configuration $C_L$ we obtain a set of configurations $\{C_1\}$ that fulfill the condition given by formula (1). The set $\{C_1\}$ is called the refinement of $C_L$. E. g. refinement of the configuration $C_3 = \{3,1\}$ at third level of granularity is a set of configurations at the first level: $\{C_1\} = \{\{1,1,1,0,0,1\}, \{1,1,1,0,1,0\}, \{1,1,1,1,0,0\}\}$.

The granulation method suggested in this section takes into account practical aspects of its application in the traffic control systems. The algorithms of traffic signals control, e. g. [2], [8], utilize traffic characteristics extracted for defined regions – so called detection zones. Such zones are usually situated in particular traffic lanes, at approaches of an intersection, where passing vehicles are counted, occupancy is detected or other measurements are performed (e. g. velocity).

In the case of video detection, many detection zones may be defined within the camera field of view. Thus, the video detection readings may be directly used for cellular traffic model updating [7]. The updating process involves cells state determination in real time that enables on-line computations of the traffic parameters.

## 4. DECISION RULES FOR SAMPLING RATE SELECTION

The granules construction method, presented in previous section, is suitable for traffic state description. This traffic description method was used for induction of prediction rules that enable selection of sampling rate for video detection system. In the presented study, prediction rules were introduced for determining the vehicles queue discharge time $\tau$ . The rule can be formulated as:

$$\text{if} \quad TS \models C_L \quad \text{then} \quad \tau \in T . \tag{3}$$

The condition $TS \models C_L$ means that the registered traffic state *TS* has to satisfy the traffic model assumptions, described by cells configuration $C_L$ . The rules induction process is based on analysis of the measurements results registered for granular description of the traffic state.

Measurements are performed to observe how long the process of vehicles queue discharging lasts and to select appropriate configuration of the model that corresponds to the arrangement of the detected vehicles. The observation objective includes: recognition of vehicles locations, cells states determination and counting the time until all the vehicles leave zone of interest (e. g. approach of an intersection). Simple video detection techniques can be used for this task.

Let us make an assumption that precision of measurements is one second and let $m_k(C_L)$ denotes result of *k*-th measurement registered for traffic state *TS* described by configuration $C_L$ . Based on the measurements results, the statistics $V(C_L, t)$ are computed:

$$V(C_L, t) = \left|\{k : m_k(C_L) = t\}\right| . \tag{4}$$

The prediction rule (3) is admitted if the following condition is fulfilled:

$$\frac{\sum_{t \in T} V(C_L, t)}{\sum_{t=0}^{t_{\max}} V(C_L, t)} \geq \alpha , \tag{5}$$

where $\alpha$ is a threshold of conditional probability and $t_{\max}$ is the maximal result of all measurements. The prediction for configuration $C_L$ is defined by interval $T = [t_a, t_b]$ of time values. This interval is determined by conditions (5) and (6):

$$t^* \in T \quad \text{and} \quad \underset{t \in T}{\forall} : V(C_L, t) \geq \beta \quad \text{and} \quad t_b - t_a \to \min , \tag{6}$$

where:

$$V(C_L, t^*) = \max_{t \in [0, t_{\max}]} \{V(C_L, t)\} . \tag{7}$$

The condition introduced in (6) maximises precision of the prediction. Induction process of the prediction rules is realised until rules are determined for all configurations $C_L$ at a given granularity level *L*.

Number of rules for the granularity level *L* is equal to $(L+1)^{n(L)}$ . On this basis, it is possible to predict the time that is necessary for traffic queue discharging, if current detectors readings are consistent with model configuration $C_L$ and if the rule for this configuration is set.

The proposed method enables predictive computations of traffic parameters on the base of historical data. This method can be applied in ITS systems for travel time estimation, route selection, navigation, traffic control and management. It can be also used for prediction of traffic parameters different from discussed in this paper.

## 5. SOME EXPERIMENTAL RESULTS

In this section some experimental results are presented considering sampling rate finding for vehicles queue detection task. The assumed detection system provides an output signal that informs if there is queue of vehicles in the crossroad approach or the approach is empty. For the selected queue configurations, the discharge time is predicted and sampling rate is determined. Sampling rate indices time, when next video data registration and analysis procedures have to be executed, to check if the queue of vehicles is still present.

Experiments were carried out with the data gathered by traffic simulation using NaSch model [6]. On the basis of simulation results, tests were performed for the introduced method of queue discharge time prediction.

A part of the testing data set was used for rules induction and another part was applied for accuracy evaluation of the prediction method. The selected results of the experiment are presented in table 1.

Table 1

Results of the queue discharge time prediction

| # | $C_L$ | L | $V(C_L, t)$ | | | | | | T [s] | P(T) | S(T) [s] | E(T) [s] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | t=5 | t=6 | t=7 | t=8 | t=9 | t=10 | | | | |
| 1 | {1,1,0,1,0,1} | 1 | 0 | 4 | 4 | 1 | 0 | 1 | [6 ,8] | 0.90 | 3 | 0.10 |
| 2 | {1,1,0,1,1,0} | 1 | 0 | 0 | 2 | 5 | 3 | 0 | [7 ,9] | 1.00 | 3 | 0.20 |
| 3 | {1,1,1,0,0,1} | 1 | 0 | 2 | 5 | 3 | 0 | 0 | [6 ,8] | 1.00 | 3 | 0.10 |
| 4 | {1,1,1,0,1,0} | 1 | 0 | 4 | 2 | 3 | 0 | 1 | [6 ,8] | 0.90 | 3 | 0.10 |
| 5 | {1,1,1,1,0,0} | 1 | 0 | 0 | 1 | 6 | 2 | 1 | [7 ,9] | 0.90 | 3 | 0.10 |
| 6 | {2,2,0} | 2 | 0 | 0 | 1 | 6 | 2 | 1 | [7 ,9] | 0.90 | 3 | 0.10 |
| 7 | {2,1,1} | 2 | 0 | 10 | 13 | 12 | 3 | 2 | [6, 9] | 0.95 | 4 | 0.08 |
| 8 | {3,1} | 3 | 0 | 6 | 8 | 12 | 2 | 1 | [6, 9] | 0.93 | 4 | 0.03 |

This example includes prediction for five different configurations of the model ($C_L$) at the first level of granulation (#1-#5) as well as for three configurations at higher levels (#6-#8). The higher-level configurations were derived using zooming-out operation. Dependencies depicted in fig. 3 show how the first-level configurations form the configurations at higher levels.

The time intervals T, presented in table 1 determine prediction results for each configuration. Size of these intervals (precision of prediction) is denoted by S(T). All values are given in seconds. The rules induction process took into account results of 10 measurements for every rule.

The following threshold values were assumed: $\alpha = 0.9, \beta = 0.1$. Values P(T) correspond to the left side of equation (5) that describes conditional probability $p\left(m_k(C_L) = t \mid C_L = \{c_{i,L}\}\right)$ computed for results of all measurements. Mean error of prediction E(T) was determined for accuracy evaluation of the proposed method, using additional traffic data.

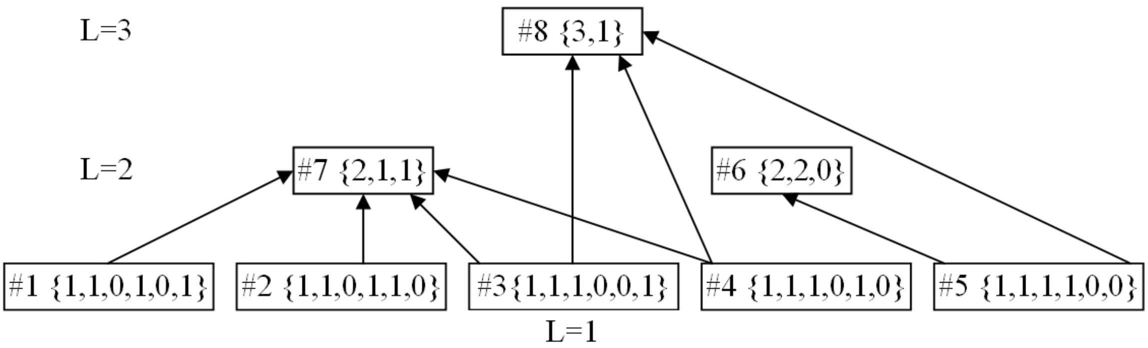


Fig. 3. Dependencies between model configurations at different levels of granulation
Rys. 3. Zależności pomiędzy konfiguracjami modelu na różnych poziomach granulacji

Accuracy of the prediction is higher for rules extracted at higher level of granularity, because the traffic description using larger cells (granules) is more general than configurations of small cells. For higher granularity level the rule is extracted from larger data set than in case of lower granularity level.

These facts are connected with lower precision of rules extracted at the higher level. The trade-off between accuracy and precision has to be considered when granularity level is selected. In practical applications the task of granularity selection for traffic model is realised by determination of the detection zones. Thus, the presented method may be used for evaluation and optimisation of the vehicles detection zones assignment.

On the base of prediction results the sampling rate can be selected for the discussed queue configurations. For all inducted rules of prediction, the queue discharge time is longer than 5 seconds. Thus sampling rate in this case is set to 5 seconds. In typical constructions, the sampling rate is lower than 1 second and constant. This fact shows us how the proposed method can be used to reduce the data amount analysed in video detection system.

## 6. CONCLUSION

The introduced method enables us the sampling rate for a traffic video detection system finding. It allows us to reduce the data amount analysed by video detection unit. The sampling rate finding algorithm is based on prediction of the traffic parameters. The prediction rules are extracted from a traffic data using granular computing algorithms.

The input data for the rules induction algorithm is registered in detection zones that are modelled as cells. Size of the cell (granule) is different at different granulation levels in the traffic model. Transformations between granulation levels are defined by zooming-out and zooming-in operators.

Presented application of the sampling rate finding algorithm confirms that this method provide the controlling unit the amount of the data relevant to the process time schedule. Simulation results shows us the method effectiveness and reliable prediction results. The precision and accuracy of prediction can easily be re-set by selection of granularity level.

The sampling rate selection method is suitable for applications in video detectors for traffic control and management. Further research investigations concern numerical implementation of methods for video detection equipment evaluation.

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