COMPUTER SUPPORTED ESTIMATION OF INPUT DATA FOR TRANSPORTATION MODELS

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Control and management of transportation systems frequently rely on optimization or simulation methods based on a suitable model. Such a model uses optimization or simulation procedures and correct input data. The input data define transportation infrastructure and transportation flows. Data acquisition is a costly process and so an efficient approach is highly desirable.

The infrastructure can be recognized from drawn maps using segmentation, thinning and vectorization. The accurate definition of network topology and nodes position is the crucial part of the process.

Transportation flows can be analyzed as vehicle's behavior based on video sequences of typical traffic situations. Resulting information consists of vehicle position, actual speed and acceleration along the road section. Data for individual vehicles are statistically processed and standard vehicle characteristics can be recommended for vehicle generator in simulation models.

Key words: transportation systems, simulation, optimization, input data.

1 Introduction

Transportation systems are large distributed systems with a rich variety of processes to be controlled. Control and management of transportation systems can be approached on the level of individual vehicles and transportation flows, in which case traffic simulation is mainly used to check on the system performance especially when changes of the infrastructure are planned. On the level of the whole network, optimization tasks like finding optimal routes and schedules usually help to plan and control transportation processes in the network [2]. To solve any such control task, a suitable model of a transportation system, effective optimization methods or simulation procedures and correct input data must be available. Even if the model and optimization routines may be used repeatedly, the acquisition of input data must be done repeatedly for every application and moreover, it is a costly and time consuming task.

Further discussion is devoted mainly to automatic acquisition of input data on infrastructure and on vehicle's behavior suitable for microscopic transportation models. The infrastructure data comprise also information on the shape of road sections, which is necessary for computation of centrifugal acceleration.

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The vehicle model uses data on vehicle behavior as seen in the traffic. It means that the recognition process does not evaluate vehicle dynamics itself (maximum speed, maximum acceleration /deceleration) but rather compound behavior of an “intelligent” vehicle manned and controlled by a driver. Such data can be gained from video recordings of typical traffic situations like free traffic, traffic at speed limits, approaching and passing a road junction etc.

2 Infrastructure recognition

If the topology of the network and all necessary attributes are not ready in digital form they must be excerpted from available supporting documents (drawn maps). An automatic recognition of drawn maps is schematically shown in Fig.1.

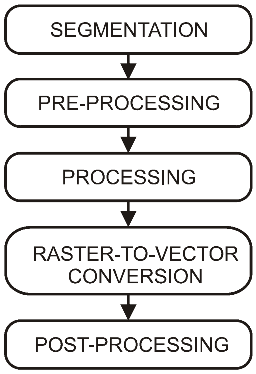

Fig.1 Stages of the general vectorization process

2.1 Segmentation

Drawn maps usually contain some background information and infrastructure data, which are of interest. Segmentation step separates infrastructure data from the rest of the map so that a binary image represents infrastructure as black pixels and all other background objects as white pixels.

The separation of line objects is accomplished by thresholding. A general decision rule for threshold can be defined as follows:

$$g(x,y) = \begin{cases} 0, & \text{if} \quad f(x,y) < T \\ 1, & \text{if} \quad f(x,y) \geq T \end{cases} . \tag{3}$$

where $g(x,y)$ is the value of pixel with coordinates x, y in a resulting binary image and $f(x,y)$ is the original value of that pixel. T is a threshold value.

Several threshold values may be used to correctly separate objects in the image. There are many local and global threshold techniques a fully automatic threshold set up method for various drawn maps can be hardly used [6].

2.2 Pre-processing

The binary image is processed in pre-processing step to remove imperfections and to amplify desired features of line objects as illustrated in Fig.2.

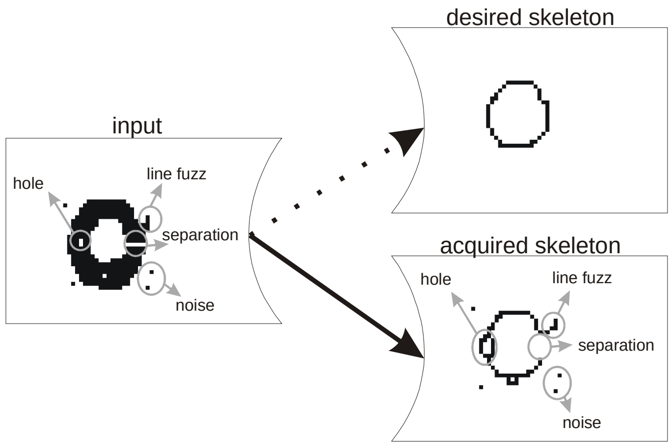

Fig.2 Desired and acquired skeleton of input image

Thinning was used to create a skeleton from an inaccurate input in Fig.2. The resulting skeleton differs from the desired skeleton because thinning is sensitive to imperfections in the original image. Accurate pre-processing for thinning removes isolated small objects, reduces boundary noise, fills small holes in objects and joins disconnected objects.

Binary morphology operators opening and closing provide very good results for this kind of tasks. Operations opening and closing can be combined to remove all mentioned imperfections [7] (of course to a certain degree only).

2.3 Thinning

Thinning algorithms remove outer pixels to produce one pixel thick skeleton. The thinning shows good results for objects like roads, the length of which is much larger than their thickness. The skeleton resulting from thinning step represents road infrastructure as a set of raster points (or a binary bitmap file) which must be further processed to yield a vector representation.

Thinning should create skeleton one pixel thick, connectivity, shape and position of the junction points should be preserved. Further, skeleton links should lie in the middle of a shape (medial axis), thinning should be immune to noise and excessive erosion should be prevented (length of lines and curves preserved).

The nature of thinning algorithms can be parallel or sequential. Parallel thinning algorithms make their decisions on deleting pixels using a bitmap from the previous iteration, while sequential algorithms use an actual bitmap.

2.4 Raster-to-vector conversion

Vectorization of road maps converts skeleton raster data to vectors representing infrastructure while topology and shape of roads must be preserved. Topology preservation means that junction points and their positions are accurately estimated and skeleton connectivity is retained otherwise false additional junction points would be created. Shape preservation includes mediality, prevention of excessive erosion and immunity to noise.

The topology and shape preservation constitutes the most serious problems, which are rarely solved accurately enough. A new method based on recognition of node candidate clusters has been proposed in [9]. A priority number is set for every cluster based on the number of 8-neighbors candidates and the number of 4-neighbors (N_4) candidates. The candidate node with largest priority is then selected for a node. The difference of local and cluster approach is shown in Fig.3.

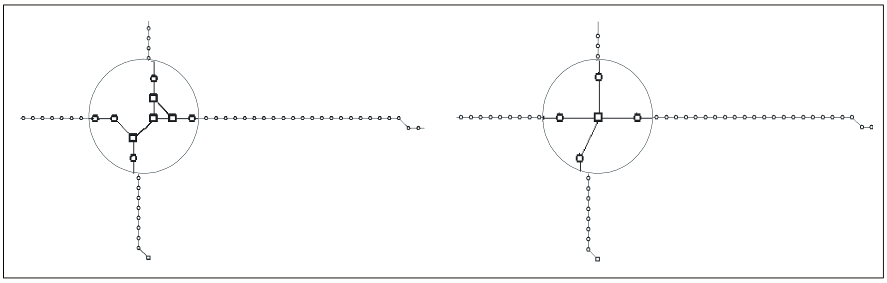

Fig.3 Local approach (left) and cluster approach (right)

2.5 Post-processing

After the raster-to-vector conversion is done vector data usually contain too many vertices which can be reduced by some kind of polygonal approximation. Also straight lines and arcs can be recognized in this phase [8]. Additional processing of vector data may include pruning, removing incorrectly separated objects, improving quality of junction points and recognition of further attributes such as length, width and color of the infrastructure links.

3 Vehicle recognition

Vehicle is a mobile object in a transportation system. The traffic surveillance or any video registering provides information on mobile objects as units consisting of a vehicle and driver and on behavior of these units in traffic. So only such manned vehicles can be recognized, which is quite relevant for simulation projects [5].

Use of such manned vehicles gives a reason why their characteristics change from case to case and must be analyzed individually. The vehicle fleet may differ substantially in various countries and also driver's behavior depends on the local tradition and practice. That is why general data are not sufficient for serious projects and specialized data should be estimated for local conditions instead.

The acquisition of vehicle characteristics from a video sequence consists of video registering of actual traffic, recognition of vehicles (moving objects), estimation of vehicle position and derived vehicle characteristics in the real world co-ordinates (scene geometry) and statistical evaluation of vehicle characteristics.

3.1 Vehicle position

A basic assumption for vehicle recognition and estimation of its position is that a camera is fixed and the scene is fixed, too (background does not change in time). This assumption is of course only partially fulfilled in practical observations. Generally, the video frames are compared to successive ones, changes between frames are recognized and evaluated. Several approaches like *background subtraction*, *temporal differencing* (differences between two successive frames) or *optical flow* can be used to find out moving objects. These methods can be programmed in dedicated applications or specialized cameras can offer a pre-processed output with recognition of moving objects.

The information on moving objects is further analyzed to estimate vehicle position and other characteristics like speed and/or acceleration. Vehicles are 3- dimensional objects and move in a 3-dimensional space while video data can provide only 2-dimensional pictures so the real world co-ordinates have to be estimated [2]. Vehicles also move on a road or (roughly speaking) in a linear co-ordinate system with only one degree of freedom and so speed or acceleration must be estimated along the road.

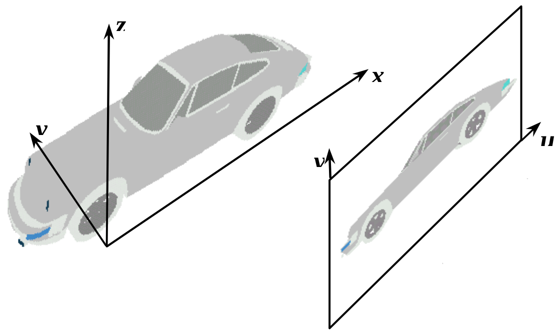

Fig.4 Vehicle 3D world co-ordinates vs. projection 2D co-ordinates

The problem of a discrepancy between a real word space and video pictures is illustrated in Fig.4. Let us denote world co-ordinates (x, y, z) and co-ordinates of video recording frames (u,v). The camera delivers a perspective projection, which can be described by a projection matrix $\boldsymbol{P}$, so that projection co-ordinates (u,v) can be estimated from world co-ordinates (x,y,z) using equation

$$(u, v, h) \leftarrow (x, y, z, h) * \boldsymbol{P}_{3,4} \tag{2}$$

where (u, v, h) and (x, y, z, h) denote homogenous co-ordinates (completed by scaling factor h). The opposite calculation symbolically denoted as

$$(x, y, z, h) \leftarrow (u, v, h) * \boldsymbol{P}_{4,3}^{-1} \tag{3}$$

cannot be done as $\boldsymbol{P}$ is not a square matrix and so an inverse matrix does not exist.

3.2 Statistical evaluation

Estimated vehicle characteristics are based on recognition of the actual speed. Its absolute value is usually less important than relative speed changes along the road, which give some insight into driver's behavior and have a significant effect on the performance of a simulated system as a whole.

The absolute speed can be calibrated fairly accurately using information on total length of the road section measured for example from the known landmarks and time calculated by counting video frame time intervals.

Statistical analysis of estimated vehicle characteristics delivers expected speed and acceleration at various traffic situations. The values measured in real traffic can be then used for vehicle generator in simulation models where every mobile unit is represented as an "intelligent" vehicle controlled by a driver.

Statistical values such as average value and standard deviation should be estimated for a set of individual vehicles at basic traffic situations. These values can be then used as input parameters for vehicle generator in a simulation model. The vehicle generator generates individual vehicles with expected characteristics corresponding to real traffic data.

4 Conclusions

Methods of data acquisition on network infrastructure and vehicle dynamics are discussed in the paper. The vectorization of infrastructure data conserves connectivity and shape of line objects in drawn maps. The operator must set up some parameters at the beginning of the process while further processing and raster-to-vector conversion run automatically.

An automatic acquisition of data on vehicle dynamics is very attractive as it offers fast and fairly cheap way of data processing. On the other hand, the derivation of all necessary equations and relations between co-ordinates, estimation of expected accuracy and elimination of errors represents a difficult task demanding high level of engineering as well as mathematical knowledge.

More work and experiments must be done to recognize real needs of data precision and expected accuracy of vehicle characteristics. Recommendations on proper camera positioning may lead to satisfactory and reliable results. A possible way to accelerate the experiments (which may be expensive in real world) is to use simulation models allowing easy change of a camera position for tests. The estimated vehicle characteristics can be stored and statistically evaluated to deliver appropriate input data for vehicle generator in a simulation model.

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