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Automatic estimation of the brightness changes for background suppression methods used for video tracking of vehicles

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ABSTRACT

One of the typical distortions in the background estimation methods is a change of lighting conditions, since each such change influences on the luminance of pixels in the captured images, which may be classified as the background. The global changes are relatively easy to compensate, but in practical applications the character of most of such changes is rather local. These changes may be caused e.g. by clouds, moving large objects, street lamps etc. Nevertheless, their influence on the results of the background estimation should be reduced therefore a local adaptive correction algorithm, applied as the pre-processing step, is proposed in the paper, assuming known geometrical configuration of the observed road

KEYWORDS: background estimation, video tracking, image analysis

1. Introduction

Intelligent Transportation Systems (ITS) are crucial for the improvement of traffic and road safety. An effective choice of the measurement, controlling and executive subsystems allows improving numerous traffic parameters. Nevertheless, even the most "intelligent" algorithm or system requires the acquisition of data being the input for the implemented procedures. Such data can be acquired using various types of sensors [1]. In the ITS solutions various sensors can be applied for measuring various quantities, often depending on some specific requirements. Probably the most typical are radar sensors, inductive loops, and Weight-in-Motion (WIM) sensors.

One of the most rapidly developing technology applied in the ITS solutions is the video analysis. The video based systems allow conducting the analysis of the traffic state on the road simultaneously for much larger area than using traditional point sensors. Hence, the number of sensors mounted inside the road may be reduced. The replacement of such built-in sensors may be expensive and cause damages of the road surface. The estimated sensors' lifetime may be equal to several years considering various factors e.g. fatigue and corrosion. In the case of the damage or failure of a camera, its replacement is relatively easy without the necessity of direct affecting the road infrastructure. Besides, the information acquired by the cameras related to the situation on the roads are easily interpreted by observing people. It can be important e.g. in the case of an accident, traffic jam or some other atypical traffic states.

The ITS video systems can be applied for the analysis of relatively large area and their working range and possibilities depend mainly on the applied algorithms. The hardware part of the system plays an important role as well but in modern systems some of their limitations are related mainly to the software. In such systems the measurement properties of the sensor (camera) can be extended by some modifications of the digital image processing and analysis algorithms, especially related to the image recognition. Nevertheless, a significant disadvantage of such systems is their sensitivity to weather and lighting conditions.

The video based analysis of the traffic state is usually conducted for the working range no longer than several meters from the camera, which can be mounted on some pylons, gates or buildings. The estimated parameters are associated with individual vehicles. The analysis of some larger areas requires the camera to be mounted at a greater height over the road. The side location cameras can also be considered assuming the specified observation angle. Both solutions are interesting but the choice depends on the character of the observed road and its surroundings as well as the specific requirements. The increase of the working range allows better prediction of some situations for distant places (e.g. traffic jams) considering the typical relations between the distance and time. The estimation based on the images acquired from distant cameras can be considered as related to the individual vehicles or the approximation for the groups of them.

The output results of tracking systems based on the analysis of image sequences are the motion trajectories of the vehicles. In order to obtain them typically some pre-processing of acquired image data should be conducted. These operations are usually related to the correction of geometrical distortions as well as background estimation for detection of the regions of interest (ROI) representing the moving objects. Then, the detection and tracking can be performed.

2. Background estimation

The background estimation task [2, 3] is an essential element of tracking since the suppression of background information significantly reduces the amount of data analysed in further processing steps. The main purpose of background estimation algorithm is related to the classification of pixels as representing the moving objects, which should be tracked or constant background.

The typical algorithms of background estimation are exponential smoothing filter and median filter. The first one utilises the fact that different moving vehicles stimulate the same pixels in consecutive video frames so the luminance values representing those objects can be interpreted as noise. The output values are calculated using information from numerous frames so the influence of this noise is reduced together with the increase of the tuneable smoothing coefficient. The median filter is based on the nonlinear filtration of the pixel's values from several frames being a robust estimator of the mean value. The output result can be considered as the most typical value which usually represents the background, especially if the moving objects are both darker and brighter than the background. Median filters with low computational cost are typically implemented using the pipeline approach so determining of each output value does not require sorting from the beginning of the data string. As considered in some earlier papers [4, 5] a hybrid approach can also be successfully applied where the median filter is used for the initialisation of the exponential smoothing algorithm.

The real image sequences acquired by cameras may contain two types of changes. The rapid, spatially limited changes are related to the moving objects whereas some slower luminance modifications with more global character result from changing lightning conditions of the scene. The estimated background should follow these slow changes of the whole background being resistant to the appearance of moving vehicles.

Reliable background estimation is not an easy task since operations on a large number of images is required despite of relatively low computational cost. Such algorithms typically require high amount of memory necessary for proper work in some specific scenarios, e.g. vehicles waiting at traffic lights even for a few minutes, so appropriately long memory buffer should be used. Too short period of buffered video frames may lead to the situation of misclassification of such waiting vehicles as the background. Moreover, such vehicles may be lost by the tracking algorithms even if the additional shape analysis [6] is used. It can be detected again after starting to move but its shape may be still present as a part of the background.

3. The influence of lighting changes

A longer working period can lead to some problems caused by lighting changes resulting e.g. from moving clouds, trees in the wind or shadows. The influence of shadows during several minutes can be easily observable in dense urban areas. Depending on the configuration of the road and surrounding objects e.g. buildings the shadow changes may be faster or slower.

Changes of lighting conditions cause some local changes of pixels' luminance in the current frame which can be properly interpreted by the analysis of differences between the background and the current image as representing the moving vehicle or a group of vehicles.

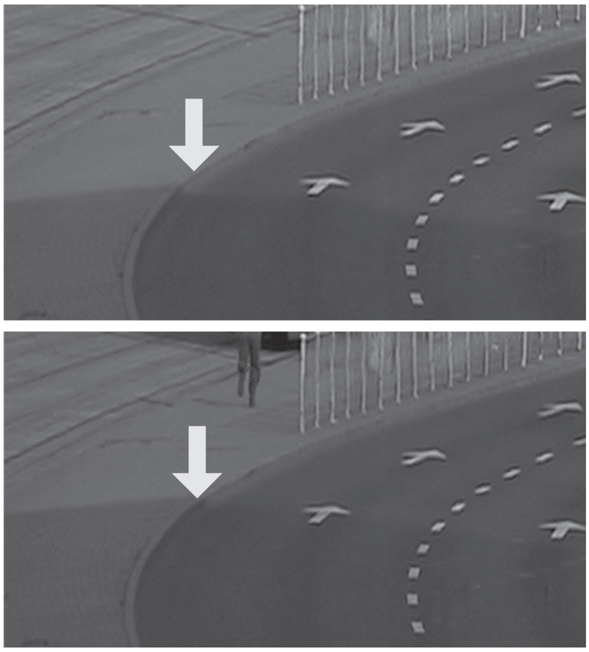

Fig.1. The illustration of the changing light conditions with marked changed position of the shadow.

Changes of lighting conditions are relevant both for long and short distances from the camera. For the closer part of the image the pixels' luminance changes caused by moving shadows are more significant since the relative speed of the shadow's motion is higher. The increase of the distance is related to the decrease of the number of pixels affected by such lighting changes. Nevertheless, the distance from the camera is not the only element influencing such changes since in fact they are dependent on the geometry of the scene. As vehicles move not necessarily on the flat roads, the additional knowledge about slopes and height of the surrounding objects may be utilised. The problem of lighting changes is illustrated in figure 1. Considering the shadow as a moving object it can also be tracked using similar methods as applied for tracking the vehicles [7, 8] with some modifications necessary for handling the slow changes also in background estimates.

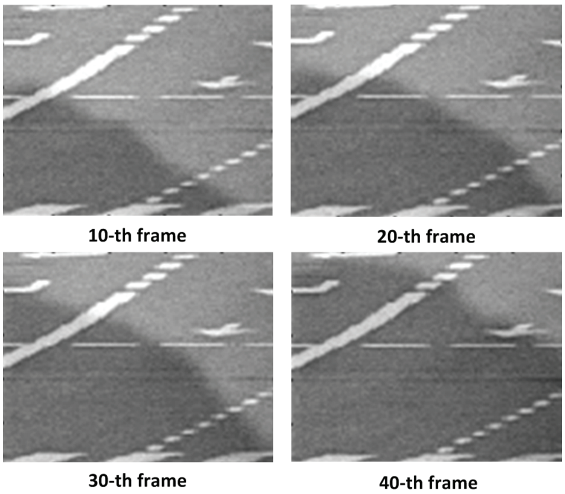

Fig.2. Some exemplary video frames of the test sequence with moving shadow.

4. The Track-Before-Detect algorithms and their application for the estimation of brightness changes

One of the solutions which may be successfully applied for vehicles' tracking is the application of the Track-Before-Detect algorithms [9, 10]. In general, the traditional tracking algorithms are based on the detection, tracking and assignment. The first part of these algorithms is the object's detection which should be conducted before the tracking and assignment, which reduce the influence of false detections or missed objects. Such approach leads to good results assuming high Signal-to-Noise Ratio (SNR) but in the presence of strong noise with low SNR values such algorithms usually fail. It is caused mainly by the sensitivity of the detection to noise which can result from the weather and light conditions, size of an object, object's variability, a long distance from the camera, or some imperfections of the background suppression.

In such conditions the Track-Before-Detect (TBD) approach [10–12] can be applied where all possible trajectories are tested at first. Then, if the cumulative object signal is high enough, the detection of the object is possible. A relevant feature of the TBD systems is also the accumulation of data over the multiple frames and/or sensors reducing the noise level.

Depending on the complexity of the trajectory two versions of the TBD algorithms may be used – the non-recurrent and recurrent one. The recurrent version has lower memory requirements and is also faster from the computational point of view. The information update formula present within the algorithm combines the input data and predicted positions whereas the motion update formula uses Markov matrix for the dispersion of probabilities (or likelihoods) between the current and future time steps. The new data is obtained from measurements and improve sharpness of the state space (probabilities or likelihoods). Depending on the value of the weight coefficient (α) the next prediction step may be based mainly on the new information (α close to 0) or the previous prediction (α close to 1). The basic algorithm can be described as [12]:

Initialisation:

$$P(k=0,s)=0 \tag{1}$$

For k ≥ 1

Motion update:

$$P^{-}(k,s)=\int_S q_k\left(s_k \middle| s_{k-1}\right)P\left(k-1,s_{k-1}\right)ds_{k-1} \tag{2}$$

Information update:

$$P(k,s)=\alpha\cdot P^{-}(k,s)+\left(1-\alpha\right)\cdot X(k,s) \tag{3}$$

EndFor

where:
s – particular space,
k – number od iteration,
X – input data,
$q_k(s_k|s_{k-1})$ – state transition (Markov matrix),
P^{-} – predicted TBD output,
P – TBD output,
α – weighting (smoothing) coefficient, $0 \le \alpha \le 1$

In the proposed solution the TBD algorithm described above can be applied for the estimation of light changes in the background images obtained using some typical algorithms. In our experiments the exponential smoothing algorithm has been used but the similar approach may also be used e.g. for the median algorithm of background estimation. The consecutive frames of the test video sequence are presented in figure 2. The results obtained during the experiments are shown in figures 3 and 4 where the state space of the TBD algorithm is presented. The detected border of the moving shadow is clearly visible in the upper and right images of the figure 4 as the shadow moves in the upper-right direction. Such obtained estimation of the light changes can also be successfully applied for the extrapolation of the changes in background estimates obtained for the next video frames.

5. Conclusion

The algorithm proposed in this paper can be an effective solution increasing the robustness of the video based ITS systems on the changing lighting conditions, especially considering the background estimation and suppression algorithms.

The future research should concentrate on the extension of the algorithm by using some extrapolation methods for the correction of the background estimation results using the shadow motion vectors obtained using the proposed method.

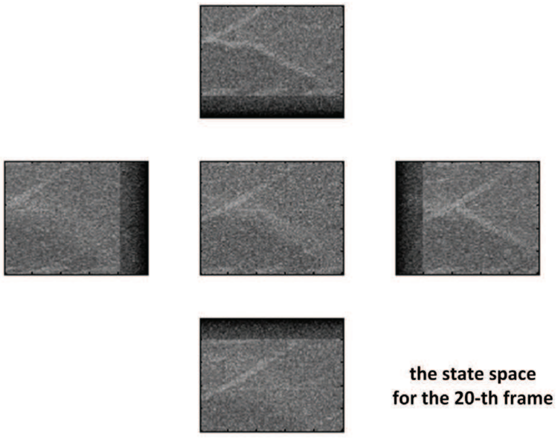

Fig.3. The state space in the Track-Before-Detect algorithm for the 20-th frame.

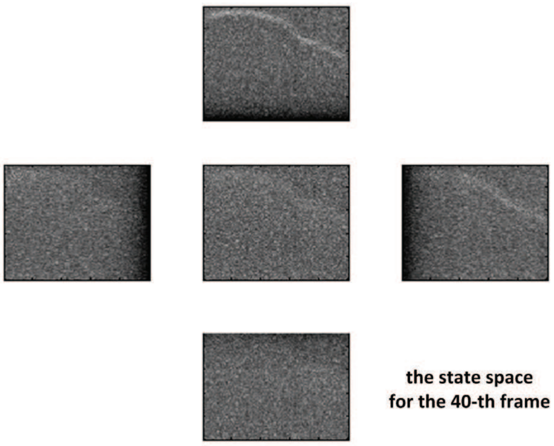

Fig.4. The state space in the Track-Before-Detect algorithm for the 40-th frame.

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