

Railway Crossing Monitoring System based on Image Processing

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Abstract—This article deals with the occupancy detection on a railway crossing (clearance detection). The presented detection is based on the optical flow estimation and classification of the flow vectors by K-means clustering algorithm. The optical flow is based on a modified Lucas-Kanade method. For testing of the developed methods a model was created and the results were verified on a real data.

Keywords—railway crossing monitoring, objects detection, background estimation, K-means clustering, Matlab, optical flow, velocity vectors.

I. INTRODUCTION

This article describes a method for objects detection in the railway crossing area. In the project SGSFEI_2014002 “The System for Image Analysis of Space Occupancy and Unknown Space Exploration” occurred the requirement for complex solution of the obstacle detection based on the surveillance camera systems. The problematic of level crossings security is strictly observed and there still continue the searching for new procedures to reduce accidents at level crossings. For these reasons a new requirement for implementation of new vision based methods originated.

The article presents a new approach to the level crossing occupancy detection. Presented occupancy status detection is based on modern image processing methods. For these purposes a new algorithm was developed for the objects and the background separating. The presented algorithm uses a modified optical flow estimation based on the Lucas-Kanade method. The objects segmentation is performed by K-means algorithm. Velocity vectors obtained from the optical flow estimation are processed in the clustering algorithm. The original algorithm for the moving objects mask estimation is based on the cumulative method and is described in detail in section III.

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In the section III is also presented the own algorithm for effective clustering of the optical flow vectors using K-means method. Finally, article contains the results of experiments.

II. RELATED WORK

The problematic of clearance detection and intrusion objects detection in the railway crossing area is primary aim in the railway crossing security [1]. In fact the objects detection is important not only in the railway crossing area. There exist many related work, for example persons detection in the train track or general obstacle detection and many others [2]. For all of these objectives is necessary to detect incoming, staying or outgoing objects in the area of level crossing [3]. Usually for the object detection are used methods based on a radar sensors multi sensor fusion or a vision based systems [4].

The common problem for image detection methods based on edge detectors is the background estimation. Application of standard edge detectors on the complicated background usually leads to the over-segmentation [5], [6].

III. VISUAL MONITORING SYSTEM

The visual monitoring system is composed of five main blocks (Figure 1). According to the block diagram is executed in parallel the optical flow estimation and the calculation of objects masks. The masks were detected by the background estimation method. The background image is an image without the cars, pedestrians and other obstacles.

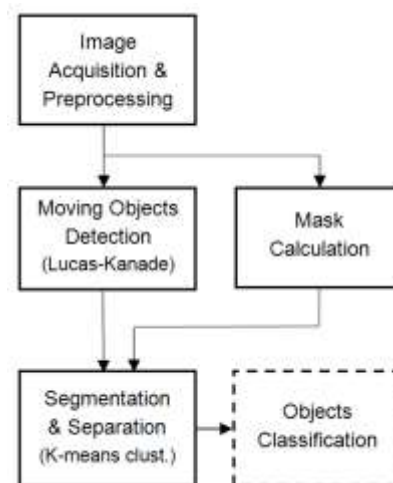


Figure 1. The block diagram of visual monitoring system

For this purpose we used the designed cumulative method [7]. Calculations were based on the acquired and adequately pre-processed data.

A. Masks Calculation

The principle of the mask obtaining is based on the subtraction of the background model from the current image I_{i+t} [8]. Using the above-obtained background matrix B_N and the current frame I_{i+t} is thus possible to obtain the matrix M at any time. The matrix M (mask) represents the dynamic objects in a scene.

$$M = B_N - I_{i+t}. \quad (1)$$

The main disadvantage of this simple approach is the significant over-segmentation. Therefore, next process is applied. The obtained mask M (*Background Estimation* method) was for the simplifying of the median-centroid calculation (for future clustering) converted to a binary image.



Figure 2. Example of centroid determination

The transformation of the mask M into a binary image was performed using thresholding (removes noise from the image). Subsequently there was performed morphological closing (removing unwanted artefacts, connects nearby objects, preserving object sizes). The whole centroids determination procedure (for next K-means clustering application) is shown in Figure 2.

The disadvantage of this procedure is the lack of information about the movement of objects. For this purpose it is possible to use the method of optical flow estimation.

B. Moving Objects Detection

Optical flow estimation is computationally demanding. In our case we chose the Lucas-Kanade (L-K) method for its advantages described in [9]. The L-K method is among the fastest and therefore most widely used methods for calculation of optical flow [10]. The L-K method introduce the error term ρ_{LK} for each pixel. This one, according to the following relation, is calculated as the sum of the smallest squares of gradient constraint in close ambient of the pixel.

$$\rho_{LK} = \sum_{x,y \in \Omega} [\nabla I(x,y,t) \cdot \vec{v} + I_t(x,y,t)]^2, \quad (2)$$

where Ω is neighbourhood of the pixel.

To find a minimal error it is necessary to compute derivation of the error term ρ_{LK} by individual components of velocity and put the result equal to zero. After finding a minimal error, several adjustments and after transfer to a matrix form the expression for the optical flow calculation is as follows:

$$\vec{v} = [A^T A]^{-1} A^T \vec{b}, \quad (3)$$

where for N pixels ($N = n^2$, for $n \times n$ of Ω neighbourhood) and $(x_i, y_i) \in \Omega$ in time t holds:

$$A = [\nabla I(x_1, y_1), \dots, \nabla I(x_N, y_N)],$$

$$\vec{b} = -(I_t(x_1, y_1), \dots, I_t(x_N, y_N)). \quad (4)$$

So we will obtain the resultant velocity for one pixel by solution of the system (3). Instead of the calculation of the sums, the convolution was used to reduce the algorithm complicacy. The Figure 3 shows an example of optical flow vectors computed by L-K.



Figure 3. The optical flow vectors estimated by algorithm LK (10)

The results indicate the dominant direction of the optical flow vectors, which well represent the moving object. On the basis of the velocity vectors is not only possible to estimate contour and occupied region but also sliding/fractional rate.

However, the problem is still a distinction between passing objects in a traffic scene. This problem was solved by application of clustering on optical flow vectors.

C. Objects Segmentation and Separation using K-means Clustering

The clustering can be performed on the optical flow vectors obtained by L-K method. Subsequently there was created the four-column matrix A (eq. 5), where the first two columns contains the pixels coordinates, the second and third the amplitude mag_{ij} and angle φ_{ij} of optical flow vectors.

$$A = \begin{bmatrix} 1 & 1 & mag_{11} & \varphi_{11} \\ 1 & 2 & mag_{12} & \varphi_{12} \\ & & \vdots & \\ 1 & N & mag_{1N} & \varphi_{1N} \\ 2 & 1 & mag_{21} & \varphi_{21} \\ & & \vdots & \\ M & N & mag_{MN} & \varphi_{MN} \end{bmatrix}. \quad (5)$$

Each row in the matrix A represents a one four-dimensional object that contains the suitable data for K-means clustering algorithm. The A matrix and the center coordinates thus represent the input data for the K-means algorithm. The outputs are then the specified coordinates for n centroids and the assignment of cluster vectors.

The used criterion for the new clusters formation was in our case, the degree of similarity between objects represented by the Euclidean distances between parameters in matrix A , for which the calculation was:

$$d_E(o_k, o_l) = \sqrt{\sum_{i=1}^n (o_{ki} - o_{li})^2}. \quad (6)$$

For our purposes was used the parametric non-hierarchical clustering - K-means [11], [12]. For the set of n vectors x_j ($j=1, \dots, n$) is performed division in to the c clusters

$G_i(i=1,\dots,c)$. The assessment function, the minimum we looking for, is defined as:

$$J = \sum_{i=1}^c J_i = \sum_{i=1}^c \left(\sqrt{\sum_{k, x_k \in G_i} (x_k - c_i)^2} \right), \quad (7)$$

where J_i are distances within one group i .

The membership of individual vectors in groups is defined by auxiliary matrix H whose elements can take the values 1 or 0 according to the relationship:

$$h_{ij} = \begin{cases} 1 & \text{if } d_E(x_j, c_i) \leq d_E(x_j, c_k), \text{ for each } k \neq i \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

After vectors assigning to the clusters, it is necessary within each cluster define a new value of the centroids. The new centroids are defined as the mean values of the vectors.

To minimize the number of iteration steps in the K-means were the initial centroids determined precisely as two-dimensional medians of detected objects mask (using the above-described Background Estimation method).

The using of non-standardized data can lead to significant errors in the calculations and, ultimately, to the loss of convergence. For this reason, the data were normalized. In our case was used the *Min-Max* normalization [13]. Additional weighting of columns in the matrix allow optimizing the behaviour of clustering algorithm.

D. Passing Objects Separation

The algorithm worked correctly in the case of completely separated objects except objects overlapping. For overlapping objects only one median – the centroid was computed. For this reason we used in described method directional properties of the optical flow vectors.

The calculated direction φ determines optical vector memberships to the *Group 1* or the *Group 2*. The groups are defined by auxiliary vector $h \in \{1; 2\}$ by:

$$h_i = \begin{cases} 1 & \text{for } \varphi(p_i) \in \langle \alpha_1; \alpha_2 \rangle \\ 2 & \text{for } \varphi(p_k) \in \langle \beta_1; \beta_2 \rangle \end{cases} \quad i \neq k. \quad (9)$$

In this α_1 and α_2 define the angle range for searching in one direction, β_1 and β_2 in reverse direction. Implemented algorithm searches for angles φ over binary mask M in the objects area. Every vector is then assigned to adequate group. The median and thus adequate centroid c_i is estimated for every group.

Functionality of the proposed algorithm is presented in Figure 2. Modified clustering algorithm works correctly in the case of overlapping objects. We are able reliable detect the overlapping objects moving in opposite directions.

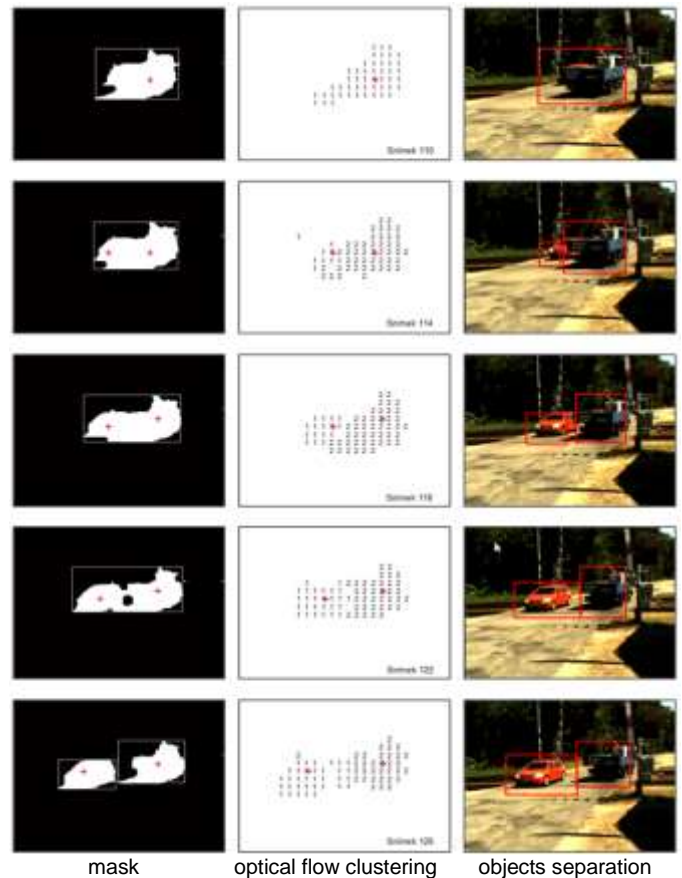


Figure 4. K-means clustering and separation of passing objects

IV. EVALUATION (TESTING)

The proposed detection method was thoroughly tested in real conditions during 2013 on two independent railway crossings in the Czech Republic.

For this purpose, the individual images were retrieved from the video sequences that have been captured by programmable Basler Scout camera from the railway crossing near village Steblova, with variable traffic density, and railway crossing Slovany, which was suitable in the city Pardubice with heavy traffic. Images from railway crossing Slovany was characterized by low quality acquired images.

For the huge amount data clustering was necessary to standardize the inputs for correct algorithm convergence. The optical flow velocity vectors have random character. Before clustering we performed the probability distribution tests on real data entering into the K-means method. During testing of probability distribution of the spatial coordinates (x, y) the uniform distribution was confirmed and Min-Max normalization has been used. Based on the probability tests results of amp and φ vectors depend if normalization will be performed.

After pre-processing, there was used the optical flow estimation (11). The outputs from the implemented L-K optical flow method were the complex velocity optical flow vectors in sparse matrix. The matrix was used to calculate the matrix A , which contains the data input to the K-means clustering algorithm. Data entering to the clustering

algorithm were finally optimized by the weighting of the normalized vectors.

The functionality of the proposed method was tested on a wide range of video sequences representing different traffic situations.

The proposed system was tested by using the obtained test data sets. The test data set consisted of video sequences acquired from various environments. The sequences were intentionally chosen to include scenes captured from different angles. The proposed algorithms were tested under different lighting and weather conditions, and in various traffic density (Table I.).

TABLE I. VIDEO SEQUENCES FOR THE EVALUATION OF THE MONITORING SYSTEM

	Length [min]	Number of objects	Lighting and weather conditions	Camera position
Sequence 1	30	284	sunny, bright light	Steblova 1 (15 m)
Sequence 2	62	296	cloudy, rain, wind	Steblova 3 (24 m)
Sequence 3	64	154	cloudy, rain, wind	Steblova 2 (25 m)
Sequence 4	58	72	cloudy, rain, snow	Steblova 3 (24 m)
Sequence 5	20	112	partly cloudy, poor video quality	Slovany (16 m)

The initial setting parameters were important for autonomous operations of the system without human interaction during the testing. This is enable objective evaluation of developed algorithms.

The main work objective was to make a more accurate and sophisticated detection and separation of individual objects to determine the number of objects, their position in the defined area and their movement directions.

Due to an objective quality assessment of the proposed methods and the whole system architecture the evaluating parameters has been defined at the start. We evaluated mainly so called System Success Rate (SSR) of the whole system:

$$SSR = \frac{\text{Num. of correct separated objects}}{\text{Total Number of objects}} \quad (10)$$

Table II. contains the numbers of correctly and incorrectly detected objects by using *BE* and *OF* method and by *K-means* method correctly separated objects in chosen *ROI*.

Obtained results calculated according to the equation (20) are shown in Figure 5. With the help of this chart it was possible to evaluate the quality of the designed system.

TABLE II. ACHIEVED RESULTS - NUMBER OF DETECTED AND SEPARATED OBJECTS

	Total number of objects	Detected objects				Correctly separated objects
		BE method		OF method		
		correct	wrong	correct	wrong	
Seq. 1	284	241	39	256	38	223
Seq. 2	296	280	24	282	26	273
Seq. 3	154	136	11	132	13	128
Seq. 4	72	70	9	68	12	66
Seq. 5	122	118	16	120	23	119

The correct function verification of proposed method was realized during real traffic (without system failure) in region of interest. The system effectiveness level (97.5 %) was proved on testing data set. In the case of improper camera placement the system still achieved the 78 % reliability. The performed tests proved that the proposed algorithms can successfully work under varying weather and lighting conditions also with low picture quality.

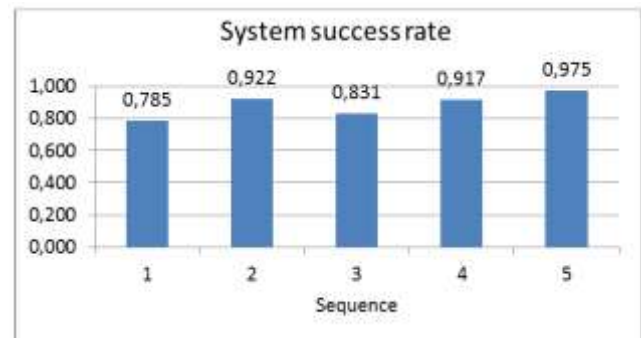


Figure 5. The success rate comparison of the system on testing data sets

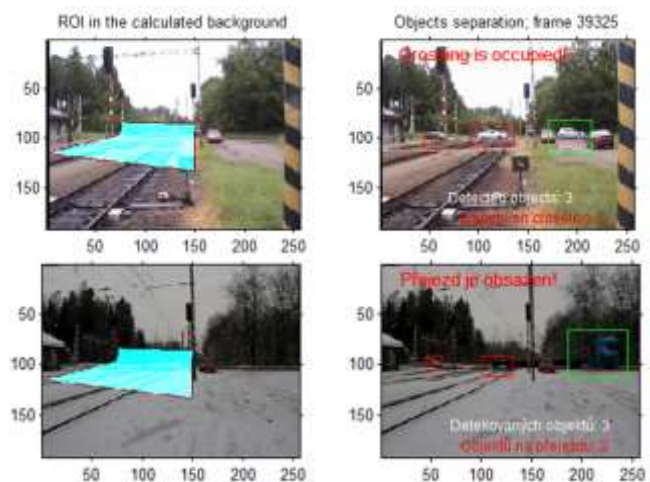


Figure 6. Examples of acceptable objects separation

The system was developed with camera position regardless, but the appropriate camera position can improve objects separation results. We situated the camera orthogonally to the railway crossing and to the movement direction of the objects. The Figure 6 presents examples of detection from the captured sequences in the case of orthogonally camera configuration. This favorable

configuration is unfortunately not available on all railway crossings in Czech Republic.

We had also the opportunity to test the robustness of the developed method, on the data acquired from industrial camera watching level crossing in the city district Pardubice-Slovany. The camera watches this dangerous level-crossing in continuous operation and the low quality images are stored on backup media for future use.

The obtained results were acceptable. The Figure 7 shows that the proposed method can be used for lower quality data.

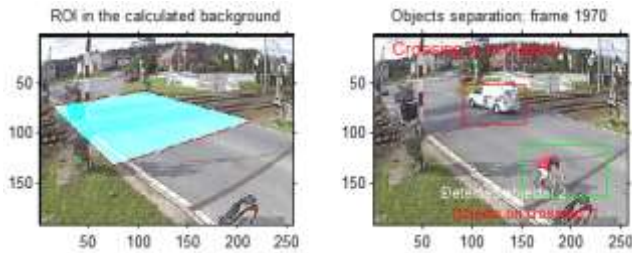


Figure 7. Objects separation over lower quality data

V. CONCLUSION

The proposed procedure allows overview and documentation detection of the railway crossing clearance. An adaptive background learning and subtraction method is proposed and applied to a real life traffic video sequence to obtain more accurate information about the intrusion objects.

Application of the Background Estimation method for the determination of centroids brought considerable acceleration and reduction of K-means iterative steps. The algorithm is able to work in a real time.

The benefit of this method is a significant improvement of objects outlines detection accuracy. The method also provides robust information about the speed and the direction of objects by application of clustering on optical flow vectors, thus it is possible reliably distinguish between objects moving in different directions.

Our method works well even in poor visual conditions. The proposed method paired with the image segmentation is robust under many situations. As demonstrated in our experiments, almost all vehicle objects are successfully identified through this algorithm. A key advantage of the proposed method is that it is fully automatic and unsupervised, and performs the generation of results by self-triggered mechanism. Hence, the proposed method can deal with very complex situations and complex level crossings.

At the present time we are working on optimization for more sophisticated classification of detected objects. Our aim is to increase the reliability of the method to a level acceptable in railway signalling systems.

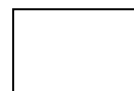
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