Moving Objects Tracking with due Account for Motion Direction and Partial Occlusions

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Abstract — **In this paper we propose a method of detection partial occlusions of moving objects that is based on agglomerative hierarchical clustering of moving objects feature points and using cluster fragmentation method that is based on watershed transformation. The main advantage of this method is a minimization of hardware resources usage and an advanced and robust efficiency of edges estimation between moving objects regions. The practical results of software implementation have shown availability of an accurate functioning in real-time mode.**

Index Terms— **tracking, moving objects, motion direction, partial occlusions problem, moving object segmentation methods, occlusion control methods, trajectories construction.**

I. INTRODUCTION

In context of digital images or digital videostreams segmentation problems, objects tracking are a part of general class of topological problems. The main application ranges of segmentation algorithms are: digital images and videostreams datamining; subtraction and recognition of objects; motion detection and management etc. Today, there are a large amount of sufficiently universal and specialized methods and algorithms, which are dealing with segmentation problem solving [9]. As far as most of these algorithms are expanded from still image segmentation methods (i.e. clusterization methods [2]), that is why their application in context of digital videostreams not always has an effective results. Especially this happens in case of recursive and iteration procedures [5]. One of the best known algorithms is a segmentation by using morphological watershed method [4]. The main disadvantage of this method is more detalized segmentation that provides a background for usage of post-processing – additional filtering procedure of segmentation results. That is why, it is relevant problem of modification the segmentation method, that will be able to remove a «noise terms» from segmentation procedure.

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II. ANALYSIS OF MOVING OBJECT SEGMENTATION AND OCCLUSION CONTROL METHODS

Tracking of moving objects is a videoframes segmentation problem, in order to subtract an objects of interest to estimate their trajectories, identify motion parameters etc. In general, videosequence segmentation can be divided to stream and frame segmentation. For a stream segmentation an end-to-end analysis of the videostream parts is determinative. In frame-by-frame segmentation, in most cases, every frame is analyzed as a separate independent digital image. This determines a practical application scope of segmentation procedures – is online systems, that are not critical to segmentation quality, frame-by-frame segmentation – is data mining systems, that are not able to function in a real time. In modern real-time videosurveillance systems videostreams with low resolution are frequent. That is why, development of videostreams segmentation methods, essentially is dedicated on modification or adaptation digital images segmentation methods. Over the last years, a lot of principally new technologies of segmentation have been developed, especially for cases of analysis of the part of real-time videostreams. The main advantage of these methods is a high segmentation quality along with low resolution videosequences.

The main segmentation methods that are used for moving objects tracking can be divided into three groups:

- statistical methods,
- structural-featured based methods,
- mixed methods.

Among statistical methods there are stochastic methods, which are based on criterion splitting of digital image by uniform regions. These methods allow creating operators to analyse frame-by-frame movement of pixels. The determinant of these methods is that they are not take into account spatial properties of motion zone. Among the most familiar methods of statistical group are:

- threshold methods [7, 25]. Threshold methods are based on fluctuation changes of the basic characteristics of videostream. That is why, their main problem is to select a threshold values and sensitivity to different fluctuations of image parameters;
- classification methods [13, 14, 20, 23, 24]. The most common is k-means etc. The main problem of classification

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methods is a machine learning [31, 32] that requires additional resources and may be a non-trivial task. In the case of iterative methods of classification their accuracy may be significantly dependent on the initialization process;

- clusterization methods [12, 15, 16, 17]. Today are one of the most developed areas of segmentation, in particular there are some well-known methods such as single link-, complete link-, average-link, Ward's-, k-means-, graph-, fuzzy-clustering etc. Clusterization methods are similar to classification methods [1, 6,]. Their main problems are: iteration scheme of criterion repetition of analysis procedure and selection of metric. In the case of agglomerative clustering methods it is necessary to perform complicated matrix operations. Some clusterization methods (such as graphs) [29] may require an initial segmentation. In terms of efficiency, all clusterization methods are not robust to noise influence, data irregularities and moving objects overlapping;

- probabilistic methods or methods with incomplete data. This group includes methods that are based on basic spatial probabilistic models of videostream. Unlike the static images, in case of videostreams there is a necessity to take into account multilevel motion models. The best known is the method of maximal likelihood and Bayesian classifier [4]. In tracking problems using probabilistic methods is limited due to complexity of frame-by-frame background subtraction;

- methods of random fields [3]. These methods are also based on probabilistic models. The best known are the methods of random fields, including Markovian fields [20]. Being stable to noise influence, these methods, are highly demanding of computing resources. Also, an efficiency of their applications depends on initial choosing of initialization model parameters, including statistical correlations between the elements of spatial plane.

Unlike stochastic, structural-featured based methods are based on feature parameters separations, that allow to take into account spatial characteristics of frame in videosequence. A group of structural-featured based methods can be divided into several classes:

- Contour methods are based on estimation and analysis of intensity function jumps. As a rule, contour methods are recursive and characterized by high stability to noise. Recently, the most popular are methods of parametric representation of contour and dynamic contour [22], that allows to predict a contour of object in videosequence. Their main limitations of these methods are low efficiency analysis of multiply connected regions, that is caused by contour curves discontinuities. The main direction in solving of this problem is a combined usage with statistical methods, dynamical contour models Bayesian classifier.

- Morphological methods are related to classical methods of objects structuring that can be determined as a result of morphological operations [28]. A characteristic feature of morphological methods is a resistance to noise and local distortion. The main disadvantage of morphological methods is a necessity of external criterion morphological processing usage. That is why, morphological methods typically used with other methods, including clusterization methods of statistical group [7, 21].

- Graph methods are based on idea of a weighted graph, where weight is estimated by the algebraic combination of intensity function values [9,10, 19, 26, 30] . The main advantage of graph methods is stability to blurred contours. But this advantage may be negated by complexity of solving the problem of graph construction.

The group of mixed methods includes: Methods based on regions analysis, immune techniques and genetic algorithms. A large amount of methods in mixed group is based on the initial usage of morphological operations. An own category in mixed group should be highlighted usage of artificial neural networks, for this category the determining is a general character of knowledge, that obtained by mixed machine learning [8].

2.2 Partial occlusion problem.

Partial occlusions of objects in videostreams are frequent phenomena that occur when key features (feature points, centroids, and boundaries) cannot be uniquely identified due to changes in forms and structures of objects. To take into account partial occlusions of moving objects, there is a necessity to solve such problems as: pixels classification to partially occluded objects [18], determination of actual position of objects trajectories, very small low contrast objects [5] and objects re-identification after occlusion. To address these challenges a number of methods of occlusion control has been purposed. Depending on way of solving occlusion problem, these methods can be divided into the following groups:

- depth maps analysis. Methods [11] creates depth maps from videoframes and analyze depth groups that are formed by the occlusions of objects. Objects that are closer to camera has a lower depth. To generate depth maps stereoscopic cameras are used [1], an estimation of probability distribution density and the usage of Kinect technology;

- image fusion. The methods presented based on ensimation of model's position and appearance of objects. A common approach to occlusion identification is an estimation of dynamical appearence model and trajectory prediction. To determine position a Kalman filter [16, 18, 23], nonlinear dynamical model [24, 25] or particle filter [26] can be used.

- optimal camera placement. Cases of objects partial occlusions can be greatly reduced by proper choice of installing cameras. For example, in videostreams from surveillance cameras with an angle of view 360°, which are mounted on the ceilings of apartments, intersections are almost absent. There is a possibility of installation more cameras to provide a greater field of view and observations areas from different angles.

III. Segmentation of moving objects

To provide moving objects segmentation an enhanced version of adaptive mixture of Gaussian distribution (MoG) is used [27]. In this Gaussian model, each pixel have a mixture of Gaussian distribution. Every pixel is classified on one of k-Gaussian distributions. Depending on the pre-defined threshold, between k-distributions, first distributions that have the largest weights are the distributions of a background pixel. In MoG algorithm the decision is made only by the statistics of the background pixels. To suppress noise influence a mathematical

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morphology operations such as dilation and erosion are used. This operation allows smoothing segmented objects. The structuring element is a set of pixels located around pre-defined pixel:

a)

b)

c)

Fig 1. Videoframe processing sequence: a – input videostream frame, b – binary mask calculation and backgroungd estimation, c – morphological processing of binary mask

$$\begin{aligned} \delta_B(S) &= S \oplus B = \{s+b \mid s \in S; b \in B\} \\ \varepsilon_B(S) &= S - B = \{B_h \subseteq S \mid h \in E\}, \end{aligned} \quad (1)$$

where: $\delta_B(S)$ - dilation of pixels in image S with structuring element B; $\varepsilon_B(S)$ - erosion of pixels in image S with structuring element B; E – discrete plane; h – vector, that determines position B on E; $B_h = \{b+h \mid b \in B\}$, - transfer of structuring element B along h. (fiq. 1)

IV. Partial occlusions detection

Partial occlusion detection of objects algorithm is based on their morphological characteristics such as fill factor, eccentricity and orientation. Let's assume that the blob that is a representation of several objects is convex, and if blob containing two or more objects, it will have a less convex shape.

Let's assume that frame at time t contains n blobs. Let's denote with Bi a set of pixels of i-th blob, pixels and with C_i a set of pixels of its contour, then the filling of *i*-th blob is defined as:

$$S_i = \frac{S(B_i)}{S(C_i)} \quad (2)$$

where $S(B_i)$ and $S(C_i)$ – area of pixels in the B_i, and C_i sets respectively.

Let denote eccentricity of i-th blob with E_i, $E_i \in [0, 1]$, and orientation of blob with $O_i \in [0, \pi]$. Orientation of blob is compared with the angle of the line, which is calculated using found sections from Hough transform. Using these characteristics, we assume that blob Bi contains more than one object if it satisfies a condition:

$$(S_i < T_s) \cup \{(E_i > T_E) \cap (E_0 < T_0)\} \quad (3)$$

where T_S, T_E, та T_O - thresholds of as fill factor, eccentricity and orientation. Thresholds are choosing empirically.

V. Clustering features points based on estimation of motion vectors

Detection of feature points is performed using Harris algorithm corners detection (Harris C. et al., 1998). Let's denote that in current frame t found M feature points. Let's create a vector of coordinates $v_i^t = [x_i^t, y_i^t]^T$, $1 \le i \le M$. If there is a point that corresponds with the corresponding point on the frame t+1, then this point is denoted $v_i^{t-1} = [x_i^{t-1}, y_i^{t-1}]^T$. Clustering algorithm of feature points consists of the following steps:

Step 1. Find a vector that defines the points of coincidence pairs:

$$V_i = \| V_{i1} \quad V_{i2} \ldots \quad V_{in} \|,$$

$$V_i = \begin{Bmatrix} 1, \mu\left(v_i^t, v_i^{t-1}\right) = 0 \\ 0, \mu\left(v_i^t, v_i^{t-1}\right) \ne 0 \end{Bmatrix} \quad (4)$$

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where μ - metric that determines proximity of points αit and αit-1; N – the size of the time window, N < t.

Step 2. Estimation of motion vectors using projection transformation matrix:

$$v_i^t = \begin{Vmatrix} x_i^t \\ y_i^t \end{Vmatrix} = \begin{Vmatrix} \frac{a}{c} & \frac{b}{c} \end{Vmatrix}^T,$$
$$\begin{Vmatrix} a & b & c \end{Vmatrix} = \begin{Vmatrix} A \cdot x_i^t & B \cdot y_i^t & C \\ D \cdot x_i^t & E \cdot y_i^t & F \\ G \cdot x_i^t & H \cdot y_i^t & 1 \end{Vmatrix} \qquad (5)$$

where $A, B, C, D, E, G, E, H \in R$.

Step 3. Estimation a set of features: $W^t = \{(p_i^t, q_i^t)\}, 1 \le i \le M$ where p_i^t and q_i^t – M-dimensional vectors that defines the movement in horizontal and vertical directions:

$$p_i^t = V_{ij} \left\| x_i^t - x_i^{t-1} \right\|,$$
$$q_i^t = V_{ij} \left\| y_i^t - y_i^{t-1} \right\| \qquad (6)$$

Step 4. Normalization a set of features – features (6) are normalized by time index *k*:

$$p_i^{-t} = K \circ p_i^t,$$
$$q_i^{-t} = K \circ q_i^t, \qquad (7)$$

where ($\circ$) partial multiplication, $K \in [M \;\; M-1 \; \dots \; 2 \; 1 \; 1 \; 2 \; M-1 \; M]$.

Step 5. Determination of the distance between two features. Measure distance is an Euclidean metric:

$$D^t(i,j) = \sqrt{\left(D_p^t(i,j)\right)^2 + \left(D_q^t(i,j)\right)^2}, \qquad (8)$$

where:

$$D_p^t(i,j) = \frac{\left(v_i^t \circ v_j^t\right) \circ \left(p_i^{-t} - p_j^{-t}\right)^T}{v_i^t v_j^t},$$
$$D_q^t(i,j) = \frac{\left(v_i^t \circ v_j^t\right) \circ \left(q_i^{-t} - q_j^{-t}\right)^T}{v_i^t v_j^t}$$

Step 6. Decision of which blob contains two objects. By the method of hierarchical accumulative clustering build two clusters of key points.

Step 7. Using method for re-identification of blob. If the condition (3) is satisfied, then go to step 1.

VI. FRAGMENTTATION OF MOVING OBJECTS AND TRAECTORIES CONSTRUCTION

For fragmentation of objects over segmentation that is based on watershed transform is used [6]. Watershed transform is a morphological method, which uses borders on images to find contours. The advantage of using of this method is that it does not require much time for computation and provides clear boundaries between the regions in the images. An assignment of fragment to one of two clusters can be estimated with:

$$V_k = \frac{\sum_{k=0}^{N} \left| I_k^{t+1}(x,y) - P_k^t \right|}{N}; \quad S_k(b) = \frac{\sum_{w_i \in C_b} V_k}{|C_b|}, \qquad (9)$$

where N – number of pixels in a fragment; $I_k^{t+1}(x,y)$ - offset of pixel in frame; P_k^t – value of pixel in a fragment; C_b – feature points clusters. If the condition is fulfilled

$$S_k(1) < S_k(2), \qquad (10)$$

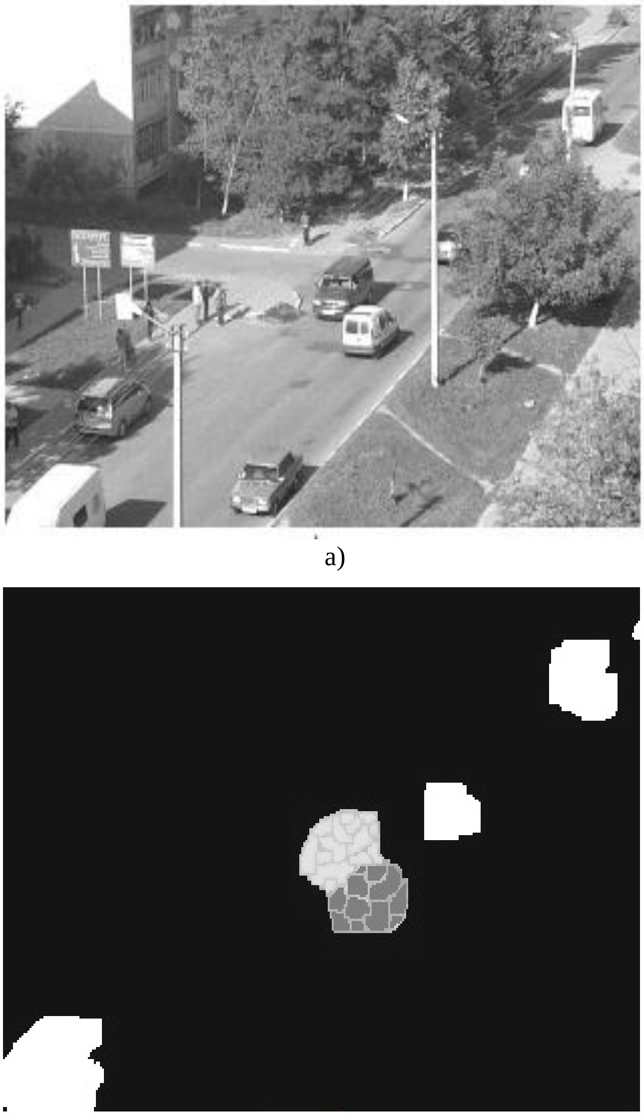
Then fragment belongs to first cluster, else to the second (fig. 2).

Construction the trajectories of occluded objects is performed using nearest neighbour method that is when each point of the trajectory to the next frame is associated with the nearest point of the trajectory of the previous frame.

For any point of trajectory can be determined the difference vector:

$$V_{i,t} = V_{i,t} - V_{i,t-1}, \qquad (11)$$

where *t* – a moment of time when *i*-th point of trajectory can be observed ($x_{i,t}$).



a)

b)

Fig.2. Fragmentation of objects during partial occlusions: a) – input frame of videosequence, b) – blob separation by fragments.

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With the difference of vectors which are in and out from point of trajectory $x_{i,t}$ can determined the smoothness of direction at this point by calculating the scalar product of these vectors and smooth speed comparison based on the average arithmetic and geometric average lengths of these vectors:

$$S_{i,k} = w\left(\frac{v_{i,t-1} \circ v_{i,t}}{|v_{i,t-1}||v_{i,t}|}\right) + (w-1)\left(\frac{\sqrt{|v_{i,t-1}||v_{i,t}|}}{|v_{i,t-1}| + |v_{i,t}|}\right), \quad (12)$$

where $w \in [0, 1]$ – weighted coefficient.

6.1 TRAJECTORIES ESTIMATION ALGORITHM.

Trajectories estimation of segmented objects, consists of such steps:

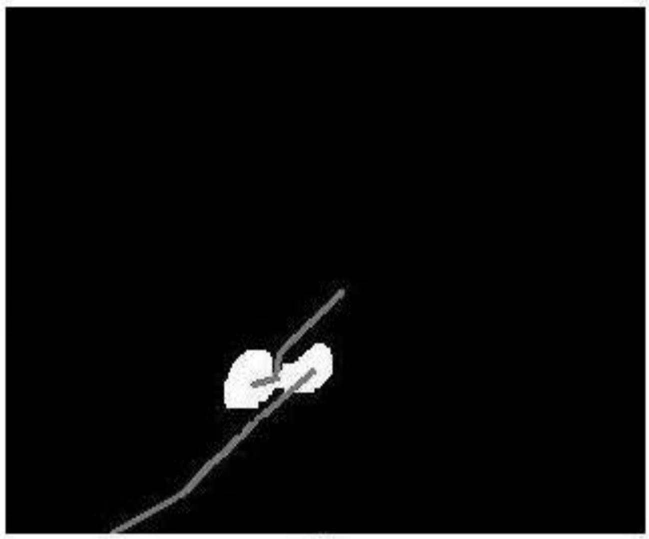
Step 1. Construct a k-parts of trajectory using a nearest neighbor points. For the first frame it is necessary to determine marking points of output array trajectories. For the next frames this assignment for each trajectory must be performed:

$$T[i, t] = n, \quad (13)$$

where n – point of i-th object in the moment of time t.

Step 2. For all pairs (i, k) determine the increase of smoothness. To provide this the cyclical exchange must be provided for each points to achieve maximum smoothness. If the exchange of points is done, then exchange flag must be set.

a)



b)

c)

Fig. 3. Trajectories estimation during partial occlusion: a) – input frame, b) – trajectories on binary mask, в) trajectories on videosequence

Step 3: If in the previous step exchanged is done, then it is necessary to reset exchange flag and repeat the loop. Result of the trajectories estimation of segmented objects you can see in fig. 3

VII. AUTOMATED VIDEOSURVEILLANCE SYSTEM

As an implementation result of software described estimation trajectory method can be stated, that the benefits of this method is that it does not require much computation time and provides clear boundaries between regions. All of this allows to use it in real-time surveillance systems.

As a result of tracking algorithm implementation, an automated videosurveillance system has been developed (Fig. 4). This system provides such features of video streaming analysis as: detecting moving objects, calculating trajectories and structure, as well as counting and calculating the direction of movement. Video can be obtained in real

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time from analog and digital cameras, as well as from video files stored on the hard drive or from DVRs. The system also includes some software utilities that are designed to quick preview of recorded videos and has video converting features

The system performs the following functions:

- support videocompression capture cards and IP-cameras;
- simultaneous view up to 16 video streams in real time at resolutions up to 1920x1080 and up to 30 FpS;
- multi-user interface with the ability to set an access rights for every individual users;
- multiscreen preview, individual settings for each video;
- support both hardware and software motion detection;
- individual settings adjustment including detection, identification of moving objects for each video stream;
- simultaneous continuous recording of each video.

Structure of automated videosurveillance system you can see in Fig. 4.

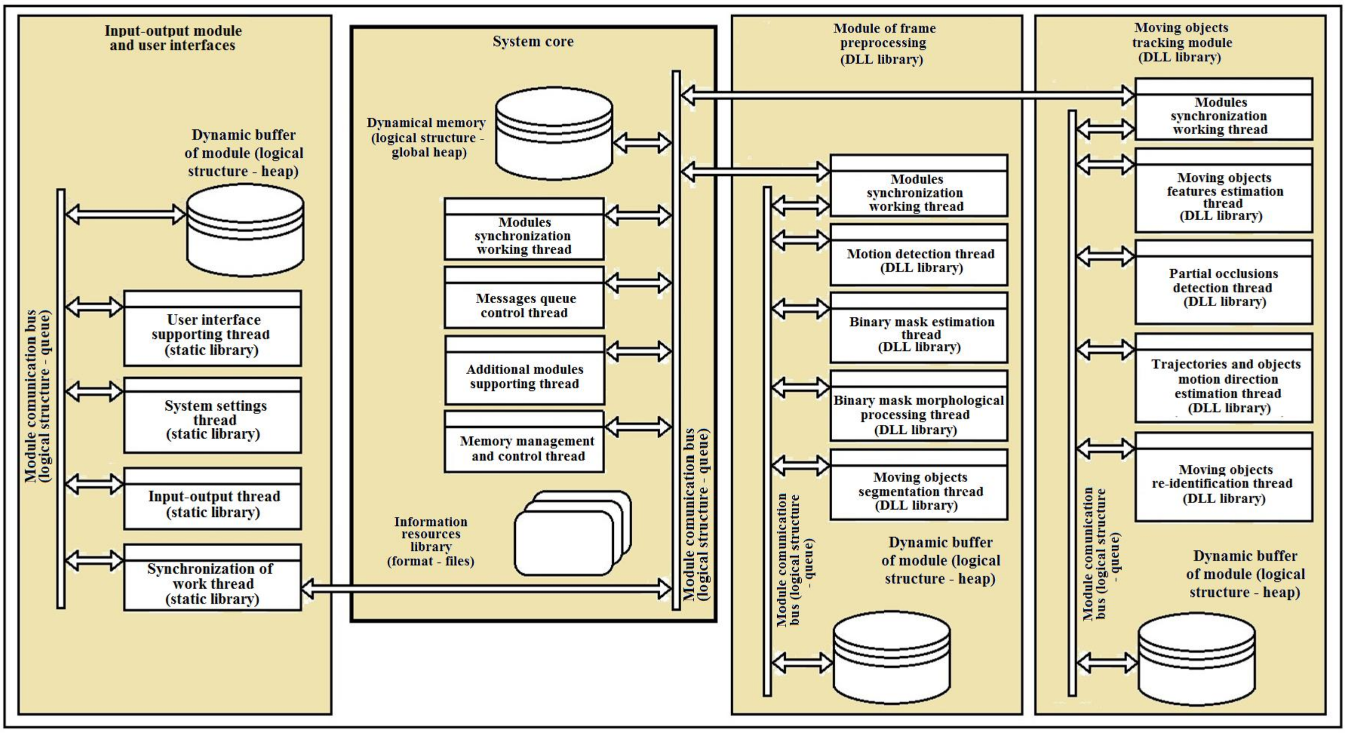


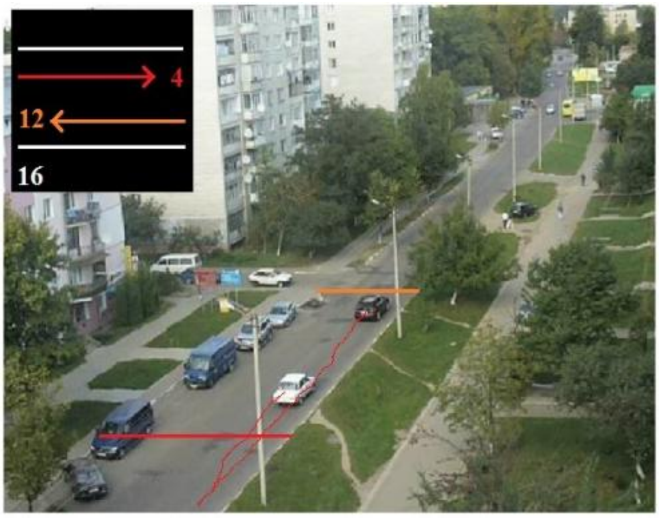
Fig. 4. Structure of automated videosurveillance system

VIII. Conclusion

Based on the described methods a software algorithm of trajectories identification in condition of moving objects partial occlusion has been developed and implemented.

The result of the algorithm is shown on Figure 5. In images 5(a), 5(b), 5(c) and 5(d) in black rectangles shows the predetermined trajectories for tracking of objects in surveillance conditions.

An algorithm is able to track all of moving objects. But some of them are removing and are not fall into account list. The numbers in the rectangles shows the objects that were moved in predefined directions and the total number of objects in observation area. Observation area is a rectangular zone defined by boundaries. There are no any restrictions to boundaries; this means that surveillance area may be whole frame of video sequence.



a)

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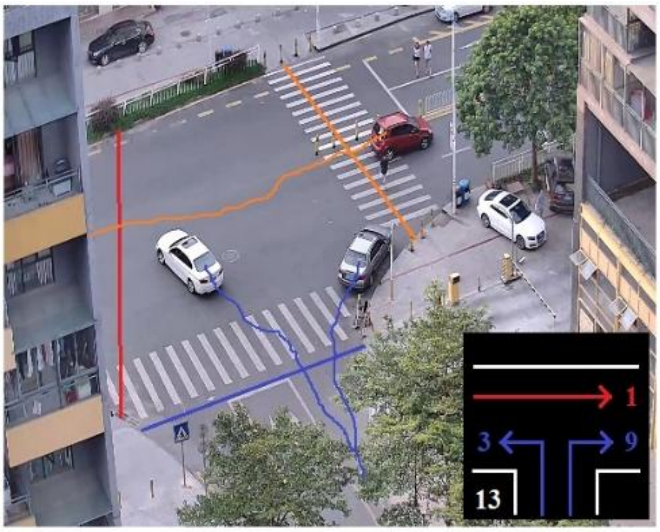
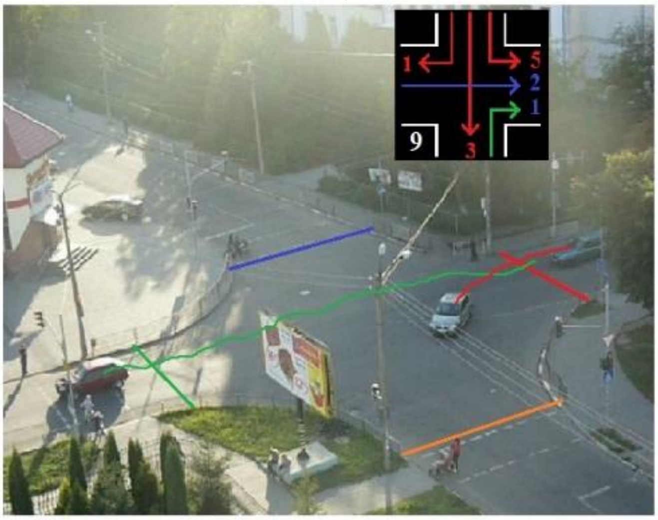
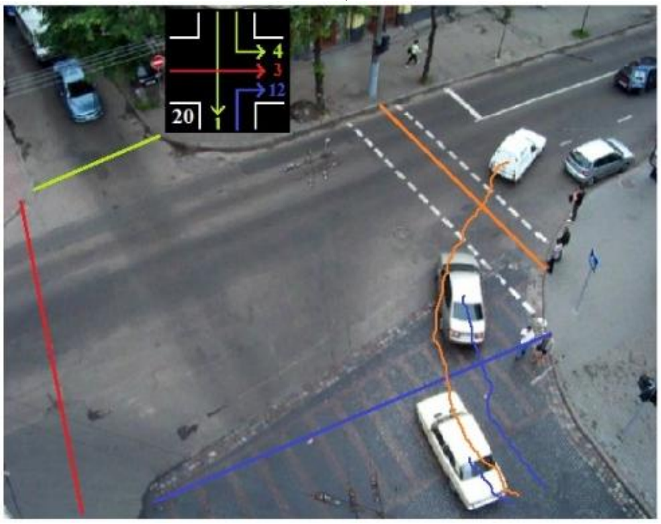


b)



c)



d)

Fig. 5. Examples of trajectories estimation of moving objects in videostreams

Trajectories account is determined by direction and by boundary of start and end of motion zone. It is allowed any variation. In black rectangles on the above figures with colored lines and arrows are indicated moving direction that are taken into account. The object is considered to move in current direction if it crossed both of borders. Otherwise, the object is not taken into account, and its trajectory is removed from list. Trajectory of the object that crossed the border area observations are not monitored. This is despite the fact that the object continue to move.

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