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Kerimkhan Bekzhan
Master of Technical Sciences, Junior Lecturer of Department of Computer and Software Engineering
bek_zhan_16@mail.ru, orcid.org/0000-0002-8480-7316
L.N. Gumilyov Eurasian National University, Kazakhstan

Zhumadillayeva Ainur
Candidate of Technical Sciences, Associate Professor of the Department of Computer and Software Engineering
ay8222@mail.ru, orcid.org/0000-0003-1042-0415
L.N. Gumilyov Eurasian National University, Kazakhstan

Nedzvedz Alexander
Doctor of Technical Sciences, Associate Professor of the Department of Computer Technology and Systems FAMS
nedzvedz@tut.by, orcid.org/0000-0001-6367-5900
Belarusian State University, Belarus

ANALYSIS OF DYNAMICAL CHANGES FROM LARGE SET OF REMOTE SENSING IMAGES

Abstract: Basic elements of changes on the multi-temporal satellite image and their basic sets of dynamic objects are formulated and defined, for which the main characteristics define the dynamic object as an area of motion. Such dependents of objects are inherited not only between objects and their dynamic groups. In such a case, the concept of dynamic objects in a multi-temporal sequence of satellite images has been developed based on the formalization of processes occurring on a change stream. A specific methodology has been developed to select a dynamic object from a dynamic group based on the analysis of the changing characteristics of the object's environment. It means that objects in a group have similar changing for separate characteristics. Such objects are included in specified ranges and are combined into dynamic groups. Characteristics dynamic group is characterized by changing every object of it. The monitoring is performed for such a group. The technique includes six stages: image acquisition and pre-processing, image scene segmentation and selection of regions, image scene analysis for segmented areas, control of compliance with the conditions for behavioral characteristics, and classification of the behavioral line of objects in the region. As a result, it is possible to describe the properties of the group's behavior and objects in the group as separate characteristics. The control of fulfillment of conditions for the behavioral characteristic is carried out to control the object as a dynamic group element. Thus, monitoring is carried out as a control for the motion of many objects rather than images.

Keywords*:* Dynamic object analysis, dynamic objects, types of movement, space images, methods.

Introduction

The distribution of satellite images has radically changed the ability to control and understand events by monitoring multi-temporal images. This has enabled many complex tasks to be accomplished, ranging from routine monitoring of transport and crop germination to resource mobilization during disasters and assessment of global warming impacts. All types of monitoring are based on the analysis of multi-temporal images, which is based on determining the most informative characteristics: color, object density, mobility, and object structure. The analysis process has the following characteristics: algorithmic complexity, computational complexity, the volume of processed data, the number of implementation stages, and the number of expected results. The most significant difficulties arise when analyzing the objects or their sets, for which the moving internal structure is characteristic. When describing the movement of such dynamic objects, it is necessary to consider the change of form, movement of the components, their division, and aggregation. As a rule, on a sequence of multi-temporal images, one can observe the movement of complexes and separate objects (which also includes the change of size and shape, for example, for ravines in case of form corrosion) and the movement of structures (change of floodplains of rivers and forest areas) (Figure 1). Despite their wide use and a large number of developed monitoring algorithms, they are difficult to process and analyze. Most known approaches are based on marking essential elements, such as the creation of objects, their tracks, and roads, which is often done manually or by semi-automatic methods.

Figure 1. Multi-temporal images for urban remote sensing images

This work proposes that mobility analysis should be performed as a single object, which will significantly speed up and simplify the analysis process.

Definition of dynamic objects

When monitoring an object, multi-temporal imaging, a sequential recording of images in long-range systems for observation and analysis, is essential, enabling a more detailed study of dynamics. The sequence of images can be considered one of the types of frame images, and its advantages include high temporal resolution and the ability to combine images over long periods. Video images provide a frame-by-frame recording of changes in the shape and movement of objects, as well as the brightness of their images [4].

Dynamic characteristics are clarified based on the analysis of several frames, which determines the interactions with each other and describes the object's behavior.

Dynamic objects are physical bodies and systems of related bodies, phenomena, technical devices, and systems of connected devices, as well as technological processes capable of perceiving external physical influences and responding to them by changing physical output values characterizing the state and behavior of the object.

In a narrow sense, dynamic objects functions in time, and their spatial parameters and characteristics are roughly considered when modeling time delays and required signals (effects and reactions) for propagation in space. Formally, a dynamic object can also be defined as an object whose model is a differential equation.

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Then all the properties that the object possesses are contained in the most differential equation in its solution. In a general case, dynamic objects are nonlinear, including they can possess discretely, for example, to change structure quickly at the achievement of influence of some level. A dynamic object is a linked group of pixels whose absolute position or shape changes during a certain time interval for a sequence of images.

A single dynamic object is characterized by changing one or all of its parameters: structure, area, shape, and coordinates.

Changes in structure, shape, and area characterize the internal changes of the object, and the coordinates describe its movement. The time interval for changing the object's characteristics can be different and marks specific points in time. As a result, these characteristics are discrete. However, the nature of these changes is usually continuous, and the differences in characteristics at different intervals may reflect the properties of the object's behavior. Objects with the same behavior can be grouped.

A dynamic group is a union of two or more dynamic objects with common properties located at a limited distance from each other. These properties, first of all, reflect the nature of the movement of objects in the group [7-8].

The nature of movement in a group can be divided into four main types:

- Directed movement of objects;
- Aggregation of objects or their groups (movement to the common center);
- Scattering of objects (movement from the center);
- Disappearance (terminator of movement).

Directional movement is determined when several objects move in the same direction.

The main signs of such movement are:

- Simultaneous movement of several objects from one area of the image to another;
- The speed of moving objects that exceeds the speed of moving objects in the background;
- Coincident directions of movement of objects.

Aggregation is the movement of objects in the direction of the common center. The movement of objects, in this case, may be symmetrical, but two directions may also prevail. The following signs of aggregation can be distinguished:

- Several objects move to one area of the image from other areas;
- The speed of movement of these objects is greater than the speed of chaotic movement;
- At least two prevailing directions can be distinguished.

Dispersion is the movement of objects from a common point in the image. Signs of scattering:

- Several objects move in a direction from their common center to other areas in the image;
- the speed of their movement is greater than the speed of chaotic movement;
- at least two prevailing movement directions can be distinguished.

Dispersion can lead to division, the formation of several new objects in the area of the location of the old group. However, this is not the complete disappearance of a dynamic object, as in this case, the objects become larger [1].

Disappearance is the terminal stage of the object's life. In this case, the object either ceases to exist or becomes dynamic. This state can be classified as a movement terminator.

These types of movement in the group determine its behavior. They are the main ones, and a more complex movement is formed on their combination, on which it is possible to predict and monitor events. More than two simultaneous images are required for quality results and forecasts.

Based on such a sequence, three levels of objects can be defined in Figure 2.

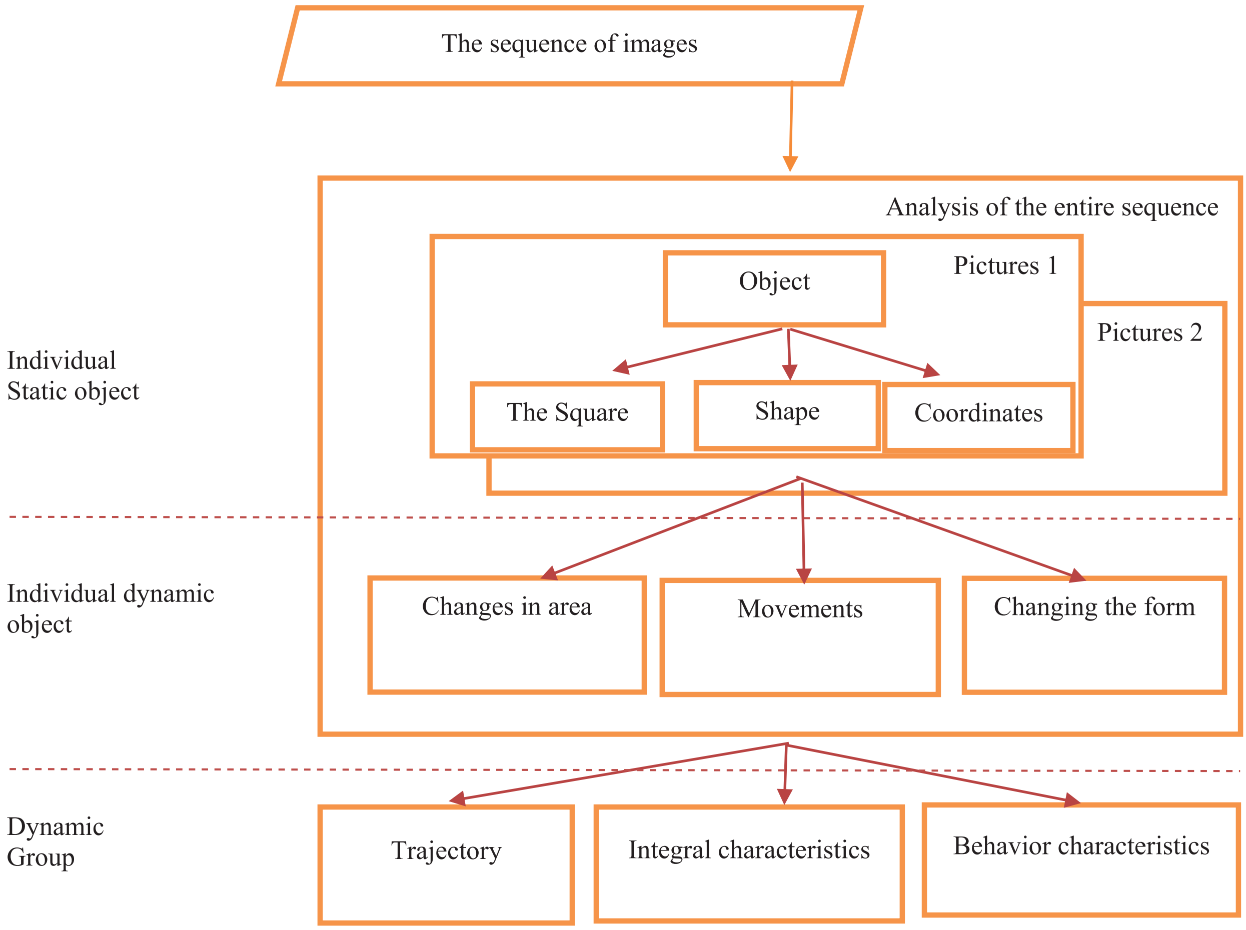

Figure 2. The scheme of the hierarchy of forming the characteristics
of dynamic objects and groups

Static objects are defined on the first level. These are monitoring objects selected in one image. In this case, their key characteristics are object coordinates, area, and shape. As soon as an image made at another time appears, we can talk about changes; in this case, the object gets dynamic status. When images are accumulated over time, a dynamic group can be formed. Dynamical groups of transport motion are shown in Figure 3.

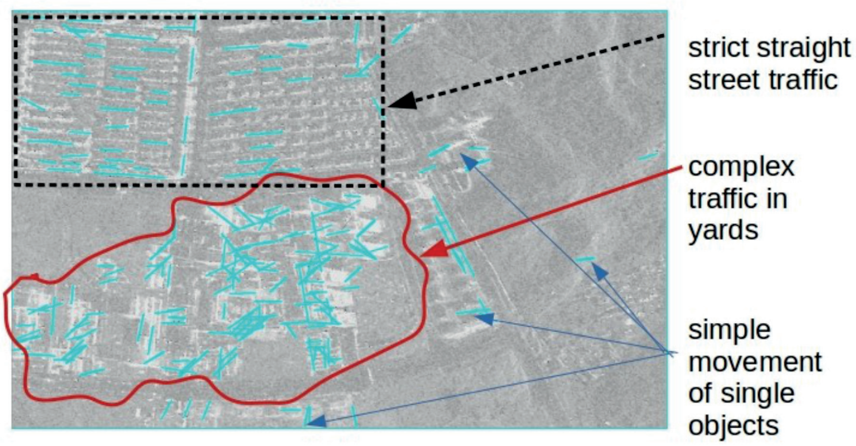

Figure 3. Dynamical groups of transport motion on Multi-temporal SAR, defined by the spread of directions and intensity of motion for neighboring objects

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The development of the idea of classical optical flow is the integral optical flow. Integral optical flow is the accumulation of optical flow vectors over several subsequent frames. As a result of such accumulation, there is a decrease in the resulting amplitudes of the background displacement vectors and an increase in the resulting amplitudes of the displacement vectors of the foreground objects. Thus, it becomes possible to reveal the chaotic nature of the background movement and identify the object's movement.

The integral optical flow for each image pixel is formed as a result of integrating the optical flow values over a given fragment of the video sequence:

$$IOF_t^{itv}(p) = \sum_{i=0}^{itv-1} OF_{t+1}(p_{t+1}) \tag{1}$$

Where OF_t is the classical optical flow for the video sequence, I IOF_t^{itv} is the integral optical flow, itv is the interval for calculating the integral optical flow, p_{t+1} is the position of the $I_t(p)$ pixel on the $t+1$-st frame of the video sequence I. In this case, $I_t(p), I_{t+1}(p_{t+1})...I_{t+itv-1}(p_{t+itv-1})$ represent the same pixel $I_t(p)$ at node *p* at different times, the values of the x-component and y -components for p are integers.

Thus, IOF_t^{itv} is a vector field that accumulates data on the displacement of pixels in the sequence from the frame I_t for the time period itv.

Restriction of the background motion and amplification of the motion of foreground objects in the calculation of the integral optical flow in the future make it possible to select foreground areas using threshold segmentation. In this case, any pixel with a sufficiently large offset vector value will be perceived as a foreground pixel.

To determine the contribution of the number of pixels and the resulting movement for each point of the trajectory, we use the normalized vector of the integral optical flow since it contains data on the number of pixels and the direction of their movement. The normalized vector $\overrightarrow{v_{norm}}$ for the optical flow vector $\overrightarrow{p_0 p_{n-1}}$ is determined by the formula:

$$\overrightarrow{v_{norm}} = \frac{\overrightarrow{p_0 p_{n-1}}}{|\overrightarrow{p_0 p_{n-1}}|} \tag{2}$$

Let θ be the angle between $\overrightarrow{p_0 p_{n-1}}$ and the *x* -axis, then the normalized vector is:

$$\overrightarrow{v_{norm}} = (\cos\theta, \sin\theta)$$

For each point of the trajectory $p_i(0 \le i < \mathrm{n})$, the following values are calculated [6-A]:

$$S_{in} = w_{in} * |\overrightarrow{v_{norm}}|$$

$$S_{out} = w_{out} * |\overrightarrow{v_{norm}}|$$

$$\overrightarrow{v_{in}} = w_{in} * \overrightarrow{v_{norm}}$$

$$\overrightarrow{v_{out}} = w_{out} * \overrightarrow{\mathrm{v}_{\mathrm{norm}}}$$

Where w_{in} w_{out} – are weight coefficients for determining the number of incoming and outgoing pixels, with $w_{in} + w_{out} = 1$. The weighting factors are calculated as follows:

$$w_{in} = \frac{|p_0 p_i^{'}|}{|p_0 p_{n-1}|'}$$

$$w_{out} = \frac{|p_i^{'} p_{n-1}|}{|p_0 p_{n-1}|'}$$

Where $p_t^{'}$ is the point of intersection of the $p_0 p_{n-1}$ line with the coordinate grid; in the process of forming the interpolated motion trajectory, its value is rounded up to p_i.

Determination of key dynamic objects on space images

Although the huge class of monitoring tasks is based on space images, the number of observed classes for dynamic objects is limited. All objects can also be divided into groups: simple and territorial objects. Simple objects include machinery, buildings, roads, viaducts, trees, bushes, lakes, streams, etc. And spatial objects may include development areas, fields, forests, water surfaces, etc. If the territorial objects have a permanent position, the position of such objects as cars may be different, as well as their presence. As a rule, a car present in the first image is not in the second image. Accordingly, it is not possible to examine the change in its characteristics. For such objects, the concept of flow is introduced, which is characterized by the way, loaded, direction, set of speed characteristics (average, integral, dispersion), and averaged characteristics of the object. In addition, the flow can describe the movement along the overpass [1-3].

The displayed image objects can be divided into textured, locally-informational, and mixed. In the class of texture images, the information content is contained in some or other macro parameters characterizing the image or a significant part of it as a whole. For the statistical description of texture images, it is natural to use classical methods and random field theory statistical models. Locally, information images are characterized by integral objects with specific geometric characteristics, and mixed images contain objects with features of both types [15-16].

Generalized scheme of object analysis methods for monitoring tasks

The general scheme of a dynamic object analysis methodology for monitoring tasks is shown in Figure 4.

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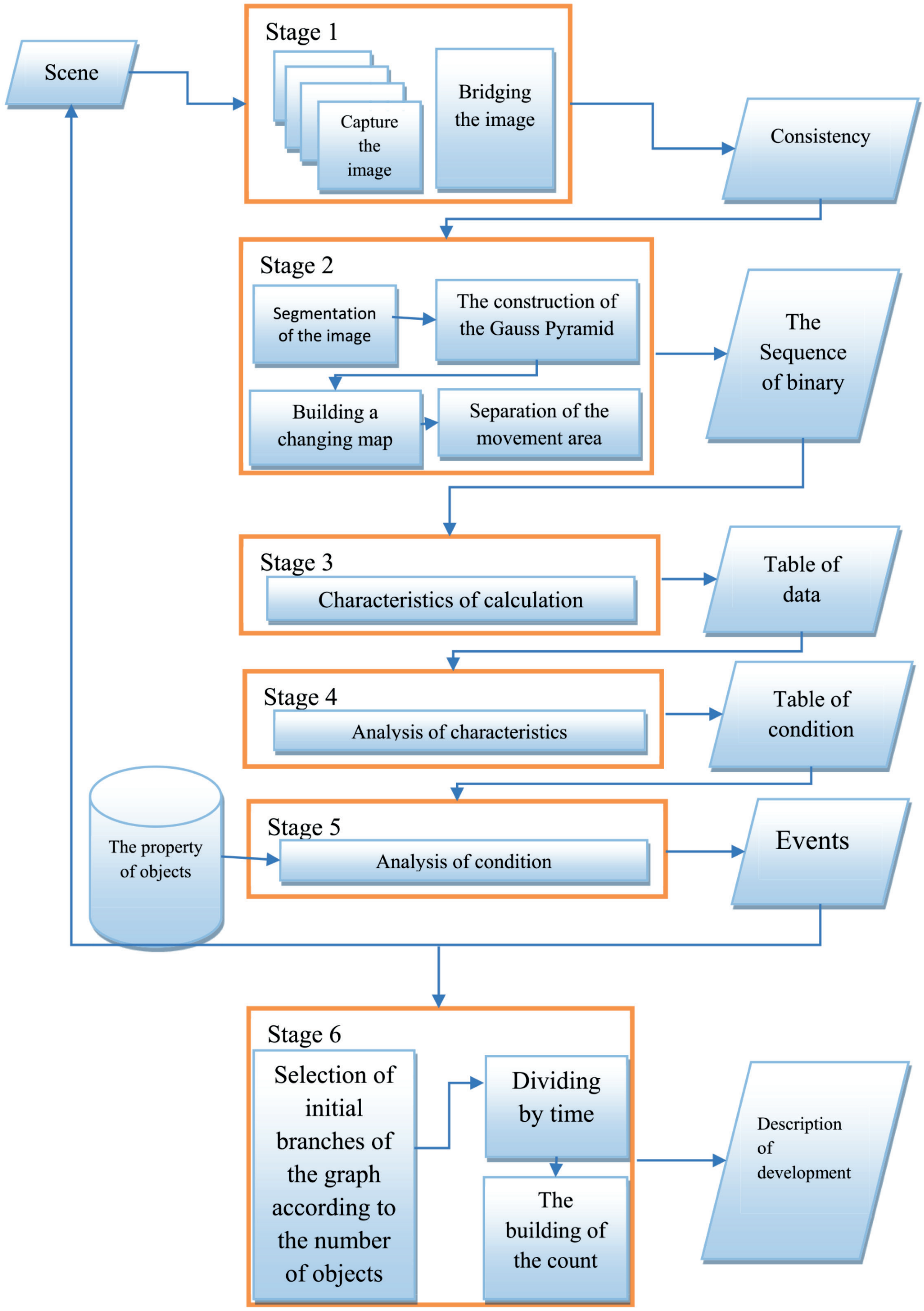

Figure 4. General scheme of dynamic object analysis methods for multi-temporal images.

The technique includes six stages: image acquisition and pre-processing, image scene segmentation and selection of regions, image scene analysis for segmented areas, control of compliance with the conditions for behavioral characteristics, and classification of the behavioral line of objects in the region [14].

The image is received and pre-processed from Internet sources according to the selected coordinates and time. Sentinel and QGIS SNAP external software package is used for image pre-processing [13].

Segmentation of the image scene and selecting areas containing the classes' main objects. There are quite a few segmentation algorithms, but the most popular and effective are networks based on U-Net architecture [3].

The neural network determines whether each point in the satellite image belongs to an object of a given class. Semantic segmentation is not just object detection. Having received the mask on the satellite image, rather large accumulations of points belonging to objects are distinguished, from which the connected areas are collected, which can be represented as polygons in vector form. The mask will not be absolutely accurate, which means that close objects can be glued together in one linked area [9]. The problem is solved either by additional network training or by an elongation algorithm. Thus, the work at this stage can be described using the scheme shown in Figure5.

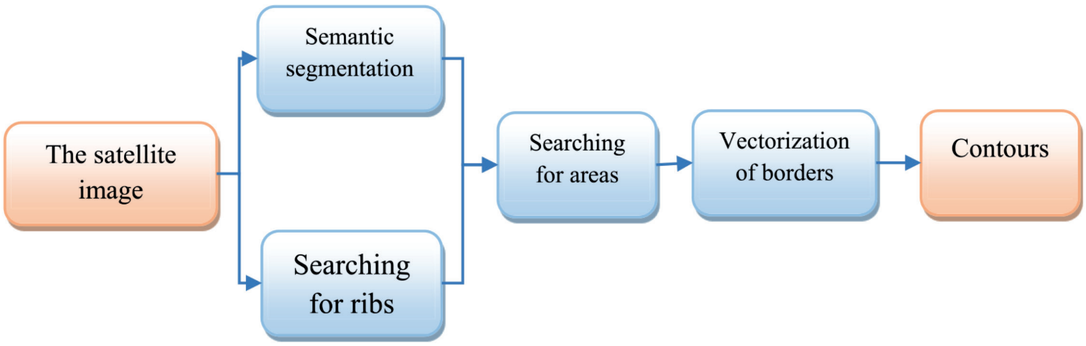

Figure 5. General segmentation scheme.

Computation of characteristics allows to formalize the object and bring it to a parametric form, as a set of characteristics, which allows to exclude it from storage image. The control of fulfillment of conditions for the behavioral characteristic is carried out to control the object as a dynamic group element. At this stage the object belonging to the group and its classification are determined. The classification of the behavioral line determines the formation of the general dynamic picture in the observed region, which is formed from the behavioral elements of dynamic groups present on the satellite images [8].

Creation of dynamic objects behavior graph on the image determines the scheme of monitoring objects behavior.

Conclusion

Based on the analysis of moving objects in remote sensing images, the elements of the basic changes are formulated and determined, which correspond to the parameters of the movement of image fragments. These base sets define changes as dynamic objects. In this case, the key characteristics of changes in an image define a dynamic object as a region of motion that is not only inherited between objects and their dynamic groups.

The concept of dynamic objects is the basis for the formalization of processes occurring on a sequence of images, is the concept of a dynamic object, which is defined as a group of pixels associated with certain common properties that remain constant over time.

For remote sensing images, these groups include objects with the same changes. For example, it can create separate dynamic groups for water objects, different types of city buildings, or agricultural fields.

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A methodology has been developed to automate the analysis of large image sets for monitoring and remote sensing tasks. It is based on the fact that each observed object is defined as a dynamic one with specified characteristics. Objects with similar characteristics or belonging to the specified ranges are combined into dynamic groups, and monitoring is performed behind the selected group.

The authors are not aware of implementations of blood flow assessment based on the video sequence. The optical flow characteristics define the dynamic properties of blood flow on video. As a result, blood vessel research is brought to a fundamentally new level, which evaluates blood flow characteristics using non-invasive methods. In this work, an original method of vessel research is based on the following:

- a new algorithm for determining the contrast area of interest;
- the original stabilization and correction of the ROI algorithm for all frames of the video sequence, based on a comparison of popular video stabilization algorithms;
- vessel segmentation that is based on the popular U-net neural network;
- original construction of a blood flow distribution map based on the Lucas Kanade optical flow, Zong-Suen thinning algorithms, and Boolean algebra methods;
- quantitative estimation of the dynamic properties of blood flow developed by the authors based on the optical flow properties.

The developed methods for analyzing the video sequence and calculating optical flow properties make it possible to quantify the change in the linear velocity of blood flow in the vessels in the microvasculature accessible for video, which shows the adequacy of the results obtained in comparison with invasive methods. The experiments performed at the Belarusian State Medical University confirm it.

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