10.1117/12.338979.

10. Kim II, McArthur B, Korevaar EJ. Comparison of laser beam propagation at 785 nm and 1550 nm in fog and haze for optical wireless communications. *Proc. of SPIE Conf. OpticaI Wireless Communications,* 2001: 26-37. DOI: 10.1117/12.417512.

DOI: 10.17725/j.rensit.2024.16.307

Criteria for image superposition in a two-camera technical vision system

Alfiya A. Diyazitdinova
Povolzhskiy State University of Telecommunications and Informatics, https://www.psuti.ru/
Samara 443010, Russian Federation
E-mail: a.diyazitdinova@psuti.ru

Received November 06, 2023, peer-reviewed November 13, 2023, accepted November 20, 2023, published April 25, 2024

Abstract: **The image superposition is the important task in machine vision system. The scene which is shot by two-camera system is the same for each camera. So the images of each camera contain the same signal. This feature defines the possible criteria for image superposition. The research tests three criteria of superposition. These are criteria by correlation coefficient, the amount of the match contour points and the amount of match feature points. The numerical simulation was developed for this research. The results of simulation identified that the correlation coefficient criteria is the most noise resistance, but it demand the greatest processing time. The amount of match contour points criteria is the least noise resistance. The amount of match feature point's criteria is better, than correlation coefficient criteria by noise resistance, and processing time is the least.**

Keywords: **criteria, superposition, two-camera system, machine vision, processing time, noise resistance, numerical simulation**

UDC 681.518

For citation: Alfiya A. Diyazitdinova. Criteria for image superposition in a two-camera technical vision system. *RENSIT: Radioelectronics. Nanosystems. Information Technologies*, 2024, 16(2):307-314e. DOI: 10.17725/j.rensit.2024.16.307.

Contents

1. INTRODUCTION

Signal processing for a two-camera system of machine vision is an important research issue. Two-camera systems are an important particular type of multi-camera systems. These systems can be used to debug various image processing algorithms for generalization to an *n*-camera system. The most well-known examples of the application of such systems are:

1. Improving image quality. Shooting a single scene using cameras with different focal lengths allows creating a high-quality image over a wide range of distances. Such a system has much smaller dimensions than a system with a mechanical change in the focal length of the lens ("optical zoom"). And such a system is characterized by higher image quality than a system with optical super-resolution ("digital zoom") [1].
2. Restoration of the three-dimensional shape of an object from two-dimensional projections (images): reconstruction of buildings, determination of the position of contact wires on tram and railway transport, restoration of human posture [2], three-dimensional reconstruction of the earth surface by unmanned aerial vehicles [3,4].
3. Reconstruction of panoramic scenes to obtain an expanded field of view compared to the field of view of single cameras [5,6].

The solution to these problems is connected with the superposition of images. Shooting by two cameras happens synchronously, the images in the intersecting fragment contain the same two-dimensional signal (note: this assumption is true if the scene is "conditionally flat" and shooting from different angles is equivalent to a homography transformation of images).

This feature defines the following criteria for superposition:

- by the maximum correlation coefficient (note: a similar criterion for the minimum of the Euclidean distance requires preliminary normalization to suppress additive and multiplicative components [7];
- by the maximum of matching contour points [8,9];
- by the maximum of matching feature points [10,11].

The superposition algorithm will have certain noise immunity and processing time depending on the criterion.

The requirements for superposition algorithms are very high. One of the requirements of the machine vision system is real-time image processing.

However, this requirement can be satisfied if, firstly, the criterion provides appropriate performance, and secondly, the signal-to-noise ratio is above a certain threshold that determines the potential noise immunity of the criterion. Otherwise, the solution to the problem with the required processing time, but for highly noisy images, cannot be obtained.

Due to these prerequisites, the relevant issues for the task of superposition are:

- recommendations making for the a criterion depending on the signal–to-noise ratio,
- prediction of processing time depending on the criterion.

This article is devoted to the research of these issues.

2. OVERVIEW OF RELEVANT WORKS

The main requirement for machine vision systems is a limited image processing time. Therefore, the researchers search various ways to increase the processing speed: reducing the number of hypotheses, using statistical and geometric features of images, switching from iterative to analytical methods.

The authors of [12,13] proposed image compression based on a "pyramid representation" in order to increase the working range of the analytical method for offset estimating based on optical flow. However, this method is used for superposing a sequence of images for tracking of a moving object. And practically it is not used for superposition images with significantly different scales.

Articles [9,14] describe a method based on the comparison of feature contour points, and the number of matched contour points is used as a metric. However, the number of hypotheses (set of feature contour points), even on a limited number of points, is very large, and the developed method can be used to solve the problem in the "post-processing" mode. The idea can be upgraded to significantly reduce processing time. Hypotheses can be formed not by brute force, but by using a preliminary matching of points using descriptors.

Algorithms [15-17] use this principle to determine an unambiguous matching between pairs of feature points. The disadvantage of this approach is high probability of incorrect matching. The probability is at least 0.05 according to a researcher by the authors.

The RANSAC (random sample consensus) method [17-19] solves this problem. It allows making a limited number of hypotheses and repeatedly reducing the probability of incorrect matching.

Among the methods that reduce the probability of incorrect matching of feature points, the technique of rejection of fragments is often used if they are uninformative. As a rule, if all pixels of a fragment belong to a very narrow brightness range, then the fragment is uninformative. An example is the dispersion of a fragment below a certain threshold [20].

Another way [21] that allows significantly increasing the processing speed is superposition by projections (the sum of brightness along the rows/columns). However, significant performance of this method is achieved only for large images.

There is a lot of research for solving the problem of increasing the processing speed for images superposition. However, they do not have a comparative analysis of noise immunity and processing speed, which depend on the superposition criterion. The main focus of the articles is the presentation of the developed algorithms, techniques and methods that allow solving an applied problem.

The article is devoted to the methodology for systematization of this field of research. The aim of the research is association defining between noise immunity, processing time and the superposition criterion.

3. SUPERPOSITION METHOD

The method [22] was developed to image superposition by the comparison of feature image points. The difference from the SIFT (scale-invariant feature transform) algorithm is the making of a point descriptor based on a log-polar transformation of the neighborhood of a feature point.

As stated before, the image superposition model is described by a homography transformation model.

The homography transformation model describe as:

$$x' = \frac{h_{11}x + h_{12}y + h_{13}}{h_{31}x + h_{32}y + 1},$$
$$y' = \frac{h_{21}x + h_{22}y + h_{23}}{h_{31}x + h_{32}y + 1}, \tag{1}$$

where h_{11}, h_{12}, ..., h_{32} are the homography transformation parameters.

The homography model is described by eight parameters. The model parameters can be estimated if the correspondence between four or more points is known (two coordinates for each point). This is necessary to make a system of linear equations of eight equations:

$$\begin{pmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x_1' & -y_1x' \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y_1' & -y_1y_1' \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2x_2' & -y_2x_2' \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2y_2' & -y_2y_2' \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3x_3' & -y_3x_3' \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3y_3' & -y_3y_3' \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4x_4' & -y_4x_4' \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4y_4' & -y_4y_4' \end{pmatrix} \times \begin{pmatrix} h_{11} \\ h_{12} \\ h_{13} \\ h_{21} \\ h_{22} \\ h_{23} \\ h_{31} \\ h_{32} \end{pmatrix} = \begin{pmatrix} x_1' \\ y_1' \\ x_2' \\ y_2' \\ x_3' \\ y_3' \\ x_4' \\ y_4' \end{pmatrix}. \tag{2}$$

One of the ways to reduce the probability of incorrect matching is geometric constraints based on the relative location of feature points in the images.

These constraints were formulated in accordance with the assumption that if four points in the first image define a convex quadrilateral, then the same four points in the second image will also be a convex quadrilateral.

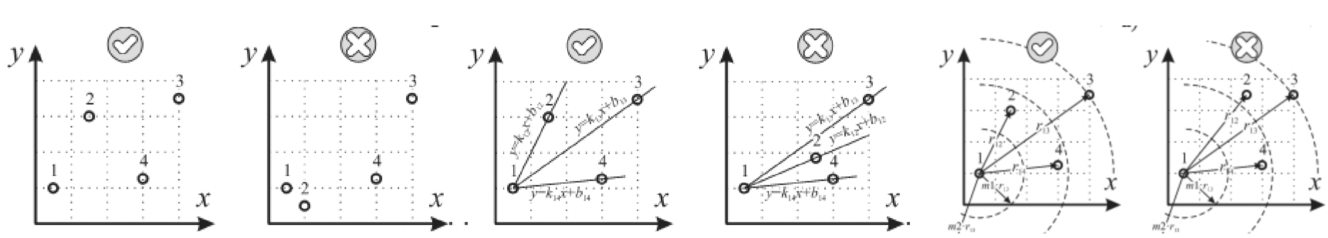
Geometric constraints are shown in **Fig. 1**.

The physical meaning of geometric constraints is as follows:

1. The constraint by location of feature points means that point "1" must have the minimum coordinate value on both axes, and point "3" must have the maximum.
2. The constraint by angle means that a line passing through points "1" and "3" must be located between lines passing through points "1" and "2", "1" and "4".
3. The constraint by distance means that the distance between points "1" and "3" (r_{13}) must be greater than "1" and "2" (r_{12}), "1" and "4" (r_{14}), as well as the distance r_{12}/r_{14} must belong to the interval $[m_1 \cdot r_{13}, m_2 \cdot r_{13}]$, where m_1, m_2 are coefficients ($m_1 = 0.4$; $m_2 = 0.6$).

The concept of "unique" feature points (part of the SIFT method) should be used to reduce processing time. If two similar fragments are present in the image in the neighborhood of the feature points, then such feature points will be removed from the analysis. This allows making only one pair of points that can be matched between images. An increase in the number of matched feature points leads to an increase in the number of hypotheses.

The RANSAC is used to exclude incorrect point pair matching that occurs during image processing. The method provides verification of only a limited number of hypotheses (note: the



a *b* *c*

Fig. 1. *Geometric constraints: constraint by location of feature points (a), constraint by angle (b), constraint by distance (c).*

number of hypotheses is limited to 100 cycles in the experiments).

4. SUPERPOSITION CRITERIA

The parameters estimation is determined by a criterion.

Three criteria were investigated in the article.

1. *The maximum correlation coefficient*:

$$\hat{\theta} = \arg\max_{\theta}\left(R(\theta)\right), \tag{3}$$

where θ is a hypothesis representing a set of transformation parameters for image superposition; for homography: $\theta = \{h_{11}, h_{12}, \ldots, h_{32}\}$; $R(\theta)$ is correlation coefficient that correspond to the hypothesis θ; $\hat{\theta}$ is estimation of superposition parameters.

The equation for calculating the correlation coefficient is

$$R = \frac{\left(\sum_{i=1}^{N} F(x_i,y_i)\cdot G^*(x_i,y_i)\right)\Big/N - \left(\left(\sum_{i=1}^{N} F(x_i,y_i)\right)\Big/N \cdot \left(\sum_{i=1}^{N} G^*(x_i,y_i)\right)\Big/N\right)}{\left(\left(\sum_{i=1}^{N} F^2(x_i,y_i)\right)\Big/N - \left(\left(\sum_{i=1}^{N} F(x_i,y_i)\right)\Big/N\right)^2\right)^{\frac{1}{2}} \cdot \left(\left(\sum_{i=1}^{N} G^{*2}(x_i,y_i)\right)\Big/N - \left(\left(\sum_{i=1}^{N} G^*(x_i,y_i)\right)\Big/N\right)^2\right)^{\frac{1}{2}}}, \tag{4}$$

where $F(x_i, y_i)$ is the first image; $G^*(x_i, y_i)$ is the second image after transformation according to hypothesis θ, (x_i, y_i) is pixels coordinates; N is the number of pixels.

2. *The maximum of matching contour points*:

$$\hat{\theta} = \arg\max_{\theta}\left(S(\theta)\right), \tag{5}$$

where $S(\theta)$ is the number of matching contour points according to hypothesis θ.

The matching contour points cannot be calculated analytically, as the correlation coefficient. The matching contour points are determined as a result of processing. The distance from each point of contour No. 1 to all points of contour No. 2 is calculated and the "nearest" is determined. If the distance between the "nearest" points is less than a certain threshold, then the points are matched.

However, calculating the distances between all points is too computationally expensive. If the point of contour No. 2 lies inside the neighborhood of the point of contour No. 1, then the points are matched (**Fig. 2**). The size of the neighborhood is determined by the threshold.

Fig. 2 shows two possible options. Two points of contour No. 2 are located in the neighborhood of contour point No. 1 in the image on the left. This means that one of them is matching. None of the points of contour No. 2 lies inside the neighborhood of contour point No. 1 in the image on the right. This means that there is no match.

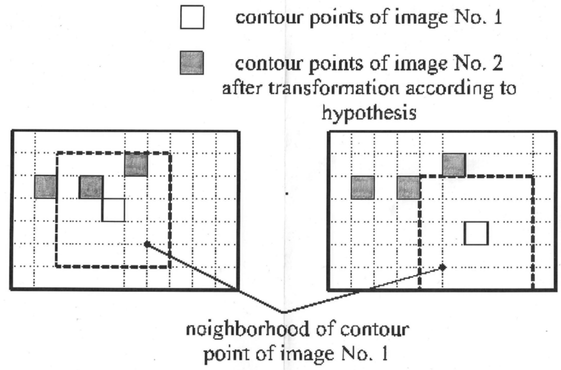


Fig. 2. *The principle of matching contour points in images: match (left) and do not match (right).*

3. *The maximum of matching feature points*:

$$\hat{\theta} = \arg\max_{\theta}\left(B(\theta)\right), \tag{6}$$

where $B(\theta)$ is the number of matching feature points according to hypothesis θ.

The number of matching feature points is determined in the same way as contour points.

5. NUMERICAL SIMULATION

The experiment included 100 images for three types of scenes:

- images with buildings which characterized by periodically repeating texture fragments (for example, images of windows);
- the surface of the earth which shoot by an unmanned aerial vehicle or a remote sensing satellite which characterized by areas with uniform brightness (note: such areas are characterized by "reduced informative");
- nature scenes (mountains, lakes, hills, etc.) which are characterized by absence of textural fragments.

An example of an image [23] with a nature scene and the result of the superposition is shown in **Fig. 3.**

The error of image superposition was determined as follows. Additive noise with a power in accordance with the signal-to-noise ratio was added to the image. And the superposition parameters were calculated in accordance with the processing procedure.

The noise power D_n was calculated as follows:

$$D_n = \frac{D_s}{h^2}, \tag{7}$$

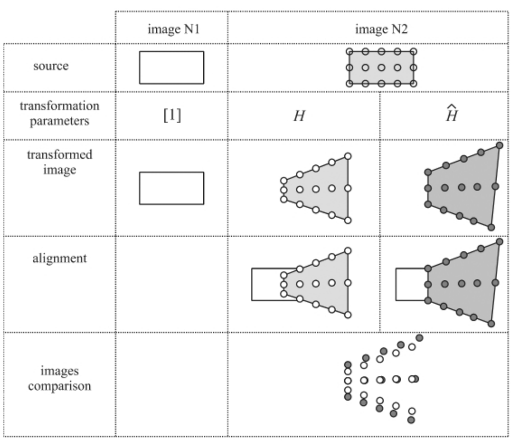
Fig. 3. *An example of processed images and a superposition.*

where D_s is the variance of brightness of image pixels, h_2 is signal-to-noise ratio.

The results of the experiment with the same noise power were averaged. Plots of the error dependence from the signal-to-noise ratio and from the criterion were made by the measurements.

The criteria were compared by a reference superposition (note: the reference superposition was determined for zero power of noise). The methodology was specially developed to estimate the superposition error.

The principle of comparing various superpositions is shown in **Fig. 4**. The original



[1] – no transform; H – reference transform; $\hat{H}$ – estimation parameters for alignment; ○ – grid point after reference alignment; ● – grid point after estimation alignment.

Fig 4. *Error estimation of superposition.*

image was aligned with the "grid". The position of the "grid" points changes according to the superposition parameters. The smaller the position of the grid points after processing will differ from the position of the points of the reference grid, the smaller the error will be. The quantitative measure is the root-mean-square value:

$$SKV = \sqrt{\frac{\sum_{i=1}^{N}\left(x_i - \hat{x}_i\right)^2 + \left(y_i - \hat{y}_i\right)^2}{N}}, \tag{8}$$

where (x_i, y_i) is grid's coordinates of reference superposition, $(\hat{x}_i, \hat{y}_i)$ is grid's coordinates after processing, N is the number of grid points.

The results of numerical simulation for three images (one from each type) are shown in **Fig. 5.**

Note: $\overline{SKV}$ is the root-mean-square value averaged for experiments with the same noise power.

The relative processing time for the criteria is shown in **Table 1**

The experiment involved images with different resolutions and different "overlap", which significantly affects the processing time even when using the same criterion. Therefore, the measurements are shown in the table in relative units, where the value "1" corresponds to the shortest processing time.

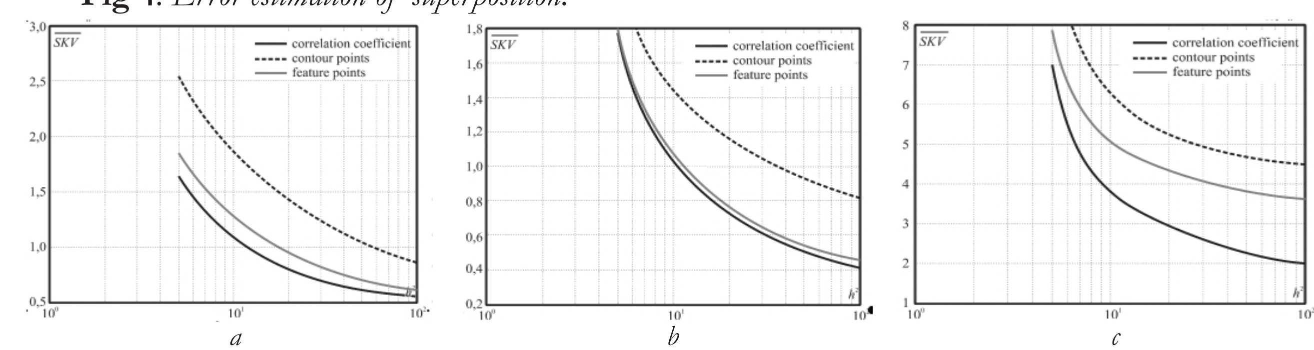


Fig. 5. *The dependence of the error on the signal-to-noise ratio for images: buildings (a), the surface of the earth (b), a scene of nature (c).*

Table 1

Relative processing time

Criterion	Maximum correlation coefficient	Maximum of matching contour points	Maximum of matching feature points
Relative processing time	500...2000	20...800	1

6. FINDINGS

The experiments allow making the following conclusions.

1. The criterion of the maximum correlation coefficient has the greatest noise immunity, and the criterion of the maximum of matched contour points has the least noise immunity.

2. The criterion of the maximum of matched feature points is characterized by the minimum processing time, and the criterion of the maximum correlation coefficient is characterized by the longest time.

3. Comparison of criteria by errors shows qualitative differences between the criteria, but at the same time it was not possible to identify quantitative values by the plots. However, a more detailed analysis of the images revealed the following patterns:

– fragments of uniform brightness (fragments with low information) have the greatest "negative" effect on the criterion of the maximum correlation coefficient; such fragments can be superpose in various ways and at the same time the influence to the correlation coefficient will be significant regardless of the superposition parameters; in other words, two homogeneous fragments can be superpose in various ways and in each case they will be similar;

– the number of contour points negatively affects the criterion of the maximum of matched contour points; in the criterion of the maximum of the correlation coefficient, each pixel of the image contains information about brightness, and set pixels define the matching of fragments, but in the criterion of the maximum of matched contour points, the more contour points, the higher the probability of random matched of points.

4. The criterion of matched contour points will be effective if the contour of the image is informative. This ensures a high-quality superposition of images. The question of informativeness estimation of the contour is open. For example, the authors of article [9] have developed a method for images superposition of the earth's surface, which allows pre-identifying contours belonging to the same object, instead of using "standard" algorithms for contour recognition [24]. Another example of the use of "informative" contours is the research for the superpose of the medical images (ultrasound images, MRI, etc.) [14]. These images contain only a single contour, which limits the human organ.

5. The most useful criterion by noise immunity and processing time is the maximum of matched feature points. The feature points are not located on fragments of uniform brightness, and the number of feature points can be automatically adjusted using a threshold to reduce the probability of random matching of points.

6. The developed method for estimation of the superposition error is universal, which compares not only different criteria, but also different superposition algorithms.

7. The developed method allows estimating the boundaries by the value of the signal-to-noise ratio at a given "permissible" superposition error for various criteria.

7. CONCLUSION

The choice of criteria for image superposition must satisfy two contradiction requirements. On the one hand, the requirement to minimize processing time means applying criteria with a minimum amount of calculations, and on the other hand, the requirement of high noise immunity means direct comparison of images, which determines the largest number of calculations.

The main result of the research is that the initial assumption that the criterion of the maximum correlation coefficient is preferable for superposition noise immunity is true only for some types of images. The criterion of the maximum of matching feature points provides in some cases almost the same noise immunity. But this criterion ensures a minimum processing time. And in most cases, this fact is a decisive argument for machine vision systems.

The second important result of the research is that it is necessary to focus on the informative features of images. A large number of contour points or processing of image fragments of uniform brightness can significantly "negative" affect the result of the superposition.

The developed methodology for estimating the error of image superposition can be used as an objective assessment tool, because the superposition parameters determine the error directly, and not indirectly.

The results will be used for further research for developing methods and algorithms of superposition for machine vision systems.

REFERENCES

1. Kokoshkin AV, Korotkov VA, Novichihin EP. Comparison of interpolation methods for achieving super-resolution of images based on the analysis of several frames. *RENSIT: Radioelectronics. Nanosystems. Information Technologies*, 2019, 11(1):85-91. DOI: 10.17725/rensit.2019.11.085.
2. Morozov AA, Sushkova OS, Hohlova MN, Min'o K, Petrova NG. Development of agent-based logic programming tools for multi-channel intelligent video surveillance. *RENSIT: Radioelectronics. Nanosystems. Information Technologies*, 2018, 10(1):101-116. DOI: 10.17725/rensit.2018.10.101.
3. Alatorcev DV, Hamuhin AV. Analiz effektivnyh metodov ocenki dal'nosti i algoritmov obrabotki videoinformacii na BPLA [Efficient methods analisys for obtaining a dense depth map and video processing onboard UAVS]. *Izvestiya Tul'skogo gosudarstvennogo universiteta,* 2020, 12:255-261, (in Russ.).
4. Kolesnikov AA. Analiz metodov i sredstv iskusstvennogo intellekta dlya analiza i interpretacii dannyh aktivnogo distancionnogo zondirovaniya [Analysis of methods and tools of artificial intelligence for analysis and interpretation of active remote sensing data]. *Vestnik Sibirskogo gosudarstvennogo universiteta geosistem i tekhnologij*, 2022, 27(3):74-94, (in Russ.).
5. Stitching panoramic images using OpenCV: https://machinelearningmastery.ru/image-panorama-stitching-with-opencv-2402bde6b46c/ (accessed 01.11.2023), (in Russ.).
6. Stitching images: https://russianblogs.com/article/39531123633/ (accessed 01.11.2023), (in Russ.).
7. Lucas BD, Kanade T. An iterative image registration technique with an application to stereo vision. *Proceedings of Imaging Understanding Workshop*, 1981, pp.121-130.
8. Paringer RA, Donon YA, Kupriyanov AV. Modifikaciya metoda sopostavleniya razmytyh izobrazhenij [Modification of blurred image matching method]. *Komp'yuternaya optika,* 2020, 44(3):441-445, (in Russ.).
9. Efimov AI, Novikov AI. Algoritm poetapnogo utochneniya proektivnogo preobrazovaniya dlya sovmeshcheniya izobrazhenij [An algorithm for multistage projective transformation adjustment for image superimposition]. *Komp'yuternaya optika,* 2016, 40(2):258-265, (in Russ.).
10. Diyazitdinova AA. Proektivnoe sovmeshchenie televizionnyh signalov metodom RANSAC dlya promyshlennyh sistem tekhnicheskogo zreniya [Homography superposition of television signals by RANSAC for commercial machine vision]. *Infokommunikacionnye tekhnologii*, 2020, 18(4):443-449, (in Russ.).
11. Bondarenko VA, Kaplinskij GE, Pavlova VA, Tupikov VA. Metod poiska i sopostavleniya klyuchevyh osobennostej izobrazhenij dlya raspoznavaniya obrazov i soprovozhdeniya ob"ektov [A method for detection and matching of image keypoints for object recognition and tracking]. *Izvestiya YuFU*, 2019, 1(203):281–293, (in Russ.).
12. Bouguet J-Y. Pyramidal implementation of the Lucas Kanade feature tracker description of the algorithm: https://web.stanford.edu/class/cs231m/references/pyr-lucas-kanade-feature-tracker-bouget.pdf (accessed 28.10.2023).
13. Smirnov SA, Babayan PV, Ershov MD, Murav'ev VS. Razrabotka i optimizaciya algoritma slezheniya za transportnym sredstvom na osnove piramidal'nogo metoda Lukasa – Kanade [Development and optimization of algorithm for vehicle tracking on video using LUCAS-KANADE method

with pyramids]. *Vestnik kibernetiki*, 2020, 2(38):58-67, (in Russ.).

14. Sungatullina DI, Krylov AS, Fyodorov DN. Bystrye algoritmy sovmeshcheniya gistologicheskih izobrazhenij [Fast registration algorithms for histological images]. *Nauchnaya vizualizatsiya*, 2014, 6(4):61-71, (in Russ.).
15. Rajalakshmi C, Alex MG, Balasubramanian R. Copy move forgery detection using key point localized super pixel based on texture features. *Computer Optics,* 2019, 43(2):270-276.
16. Konstantinov IS, Gajvoronskij VA. Razrabotka i issledovanie strukturnoj modeli postroeniya ob"emnogo panoramnogo izobrazheniya [Development and research of a structural model for constructing a three-dimensional panoramic image]. *Ekonomika. Informatika*, 2023, 50(1):133-143, (in Russ.).
17. Chekhovskij DV, Cudikov MB. Osobennosti poiska priznakov izobrazhenij dlya polucheniya panoramy iz serii kadrov [Specialties of finding image features for panoramic images made from several frame]. *Izvestiya Tul'skogo gosudarstvennogo universiteta*, 2019, 3:30-34, (in Russ.).
18. Sinicyn AV. Obzor metodov sozdaniya panoramnogo izobrazheniya dlya sistemy tekhnicheskogo zreniya [Review of methods for creating a panoramic image for a vision system]. *Stolypinskij vestnik*, 2023, 2:947-956, (in Russ.).
19. Chekanov MO, Shipit'ko OS, Ershov EI. Odnotochechnyj RANSAC dlya ocenki velichiny osevogo vrashcheniya ob'ekta po tomograficheskim proekciyam [1-point RANSAC for axial rotation angle estimation by tomographic projections]. *Sensornye sistemy,* 2020, 34(1):72-86, (in Russ.).
20. Goshin EV, Kotov AP, Fursov VA. Dvuhetapnoe formirovanie prostranstvennogo preobrazovaniya dlya sovmeshcheniya izobrazhenij [Two-stage formation of a spatial transformation for image matching]. *Komp'yuternaya optika*, 2014, 38(4):886-891, (in Russ.).
21. Krasheninnikov VR, Kadeev AD. Algoritm ocenivaniya sdviga i povorota izobrazhenij na osnove metoda nepodvizhnoj tochki [Algorithm for estimation of images shift and rotation based on fixed point method]. *Izvestiya Samarskogo nauchnogo centra Rossijskoj akademii nauk*, 2013, 15(4):931-935, (in Russ.).
22. Diyazitdinova Alphiya. Homography superposition of multidimensional television signals in improving quality images issue for multicamera video surveillance system. *Proc. of SPIE* 12295*: 19th International Scientific and Technical Conference "Optical Technologies for Communications",* pp.122950P. Samara, PSUTI, 2021; doi: 10.1117/12.2630869.
23. RANSAC Algorithm: https://stackoverflow.com/questions/4655334/ransac-algorithm?noredirect=1 (accessed 01.11.2023).
24. Canny J. A computational approach to edge detection. *IEEE Tranactions on Pattern Analisys and Machine Intelligence*, 1986, 8(6):679-698.