Parametric Methods and Algorithms of Volcano Image Processing

Sergey Korolev[1(✉)], Igor Urmanov[1], Aleksandr Kamaev[1], and Olga Girina[2]

[1] Computing Center of Far East Branch of the Russian Academy of Sciences, Khabarovsk, Russia
serejk@febras.net
[2] Institute of Volcanology and Seismology of Far East Branch of the Russian Academy of Sciences, Petropavlovsk-Kamchatsky, Russia

Abstract. A key problem of any video volcano surveillance network is an inconsistent quality and information value of the images obtained. To timely analyze the incoming data, they should be pre-filtered. Additionally, due to the continuous network operation and low shooting intervals, an operative visual analysis of the shots stream is quite difficult and requires the application of various computer algorithms. The article considers the parametric algorithms of image analysis developed by the authors for processing the shots of the volcanoes of Kamchatka. They allow automatically filtering the image flow generated by the surveillance network, highlighting those significant shots that will be further analyzed by volcanologists. A retrospective processing of the full image archive with the methods suggested helps to get a data set, labeled with different classes, for future neural network training.

Keywords: Image · Algorithm · Information system · Volcano

1 Introduction

The research and monitoring of hazardous natural sites, such as volcanoes, is a complex interdisciplinary science and technology problem. An important part in this research is given to computer systems and technology providing for the collection, systematizing [1] and a specialized information processing [2, 3], numerical modeling of various processes [4], etc. The main data source for the research is instrumental surveillance networks, which are actively used to monitor volcanic activity, too.

The unique nature of volcanoes conditioned by their geographic location, the equipment used, and scientific problems being resolved requires an individual approach towards the development of computer systems intended inter alia for the image processing. They should provide image filtering to eliminate non-informative or spoiled data as well as the search for the signs of volcano activity. At the initial stage it is important to get the sets of high-quality images which can be used for the operative control of the volcano state and for further research of certain historical events. To implement these functions, one need a complex approach and the application of various methods and algorithms of computer vision.

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The quality of the obtained shots depends on various factors. For example, the presence of fog, cloudiness or precipitation, light-striking because of sunlight as well as video equipment technical issues and data communications breaks. As a result, a corrupted image is generated, where volcano could be not clearly visible, and the evaluation of its state could be difficult or impossible. Usually, the volcano video observation systems are built with specialized hardware (for example, thermal cameras [5]). Certain research dwell upon the development of the algorithms of shot analysis made by cameras operated in the visible spectrum [6]. However, the solutions developed on their basis are usually limited by the requirement of clear object visibility. The obvious method of detecting anomalies on such shots is the search for the areas with the brightness is higher than some certain threshold [7]; still, such areas can correspond to some extrinsic illuminated objects. The neural nets that have been widely applied for image processing [8] require a large labeled training dataset and an individual approach towards the selection of optimal architectures and solutions. The manual generation of a training data is an extremely time-consuming task.

The authors are developing the algorithms and computer systems on their basis for processing volcano images generated by Kamchatka volcanoes video observation network [9]. This paper presents a partial result of this work. Using them, it is possible to conduct a basic classification for the images made during the daylight (hereinafter referred to as day shots) and reveal potentially hazardous thermal anomalies in the shots made at night with the cameras equipped with infrared-cut filters (hereinafter referred to as night shots).

2 The Volcano Day Shot Analysis Algorithm

To analyze the day shots, the estimate of the natural object contour visibility is suggested; these contours are represented as open polygons with the branch points in the vertexes [10]. First, the Canny edge detector [11] is used to calculate a discrete map of edges. Then, the depth-first search and breadth first search are used to extract branch points and contour ends (Fig. 1a) which are further connected by curves (Fig. 1b). The example of the parametric contours built is given in Fig. 2.

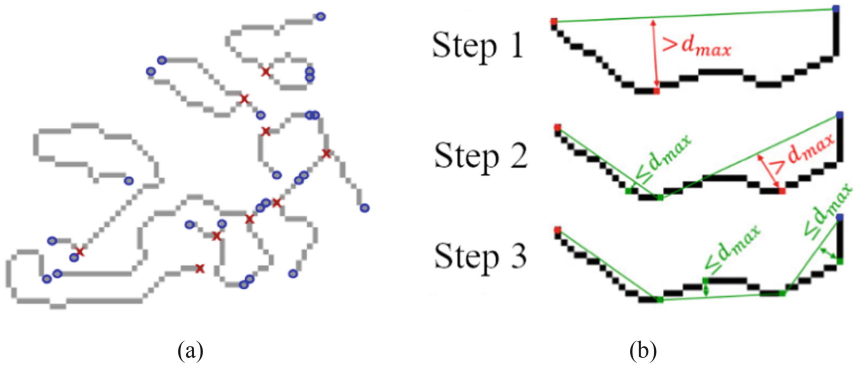


Fig. 1. Building parametric contours: a) intersection points (red crosses) and end points (blue circles); b) recursive edges build process.

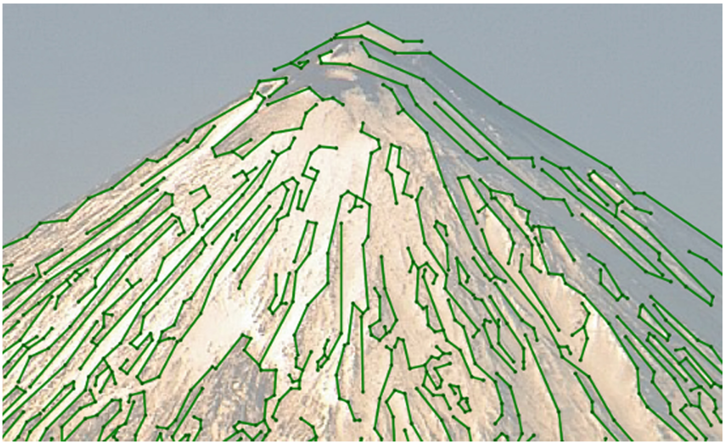
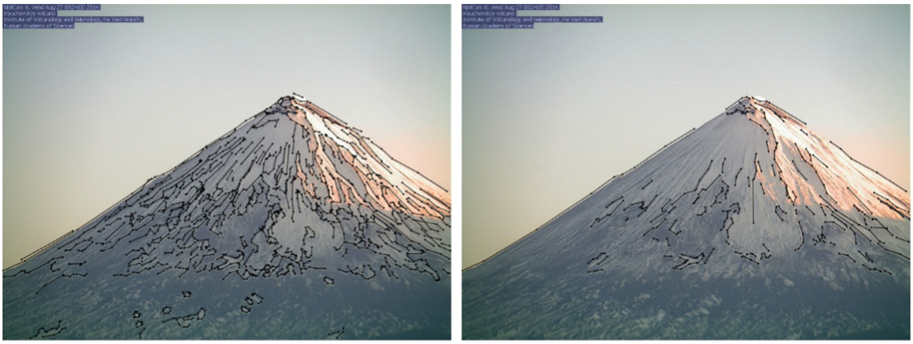


Fig. 2. Contours built for Klyuchevskoy volcano example image.

For each camera, the set of reference shots must be compiled from shots obtained in good weather and illumination conditions at various seasons. The number of reference shots in a set should be at least 10, what is significantly smaller than a necessary training set size for a neural net. The reference shot set is used to extract the reference volcano contours.

For any new given image, the object parametric contours are extracted. Then they reduced to subset, that is common for at least γ contours from reference subset (Fig. 3). To obtain the most precise estimates, a parameter γ is selected separately for each camera with the account of the number of the obtained reference contours of the considered volcano.



(a) (b)

Fig. 3. Reference contours examples for different γ.

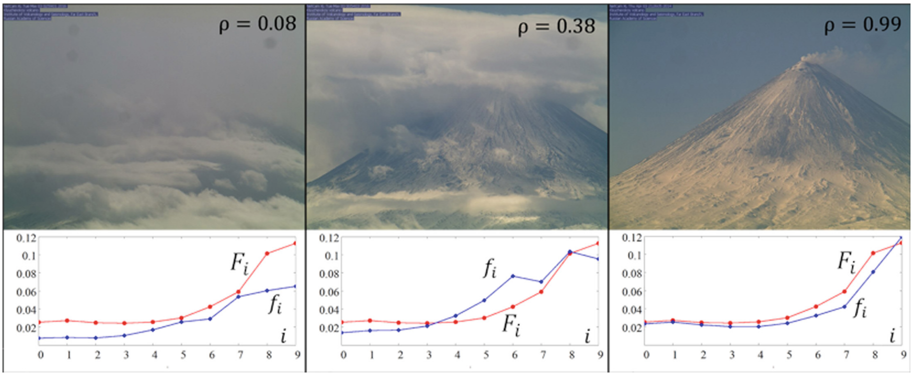


Fig. 4. Examples of frequency characteristics comparison for Klyuchevskoy volcano images taken in different weather conditions; F – octave frequency contribution vector for reference images, f – for the analyzed image.

The contours in the shots obtained the same camera can have some displacement relative to each other because of the external factors, for example, camera tremor due to the wind. To overcome that, a discrete contour comparison method is suggested [12], based on the distance map [13].

The total estimate σ of volcano contours visibility is defined by the equation:

$$\sigma = \max\left(\min\left(1, \frac{\sigma'_{ext}}{\min_{i=1,2,\ldots,m} \overline{\sigma}_{ext,i}}\right), \min\left(1, \frac{\sigma'_{int}}{\min_{i=1,2,\ldots,m} \overline{\sigma}_{int,i}}\right)\right), \tag{1}$$

where σ'_{ext} and σ'_{int} – estimates obtained by the comparison of test shot contours with external and internal reference contours respectively, while $\overline{\sigma}_{ext,i}$ and $\overline{\sigma}_{int,i}$ – estimates obtained at the comparison of contours of the i-th reference image with external and internal reference contours respectively, m – number of reference shots.

Despite some cloudiness, certain shots show clear volcano contours thus giving a possibility to detect some volcano activity signs. The estimate σ for such shots can be understated due to a poor visibility of contours considered as the reference ones. In such cases the estimate σ is corrected by the image frequency characteristics estimate $\rho \in [0, 1]$, calculated with the octave frequency contribution vector for the image brightness component [10]. As is it was done for contours, the frequency characteristics are calculated for the reference images and further compared with the corresponding characteristics of the images under analysis. Figure 4 shows the examples of the calculated frequency characteristics for Klyuchevskoy volcano images made in different weather conditions and the results of their comparison with the reference parameters.

The correction is made for the shots estimate σ which is in the Δ - vicinity of a given threshold σ, and result volcano visibility estimate is defined as:

$$\alpha = \sigma f(\sigma) + \rho(1 - f(\sigma)), \tag{2}$$

where

$$f(\sigma) = \min\left(1, \frac{1}{\Delta^2}(\sigma - \tau)^2\right). \tag{3}$$

The developed algorithm is tested at image dataset for volcanoes Sheveluch, Klyuchevskoy and Kizimen (3,000 shots for each volcano). For Sheveluch and Klyuchevskoy volcanoes the final estimate was calculated wrong (too low or too high) for 1% of images, for Kizimen – for 2% [10]. The experiments showed, that the error in volcano visibility estimate may be caused, at first, by the peculiarities of camera settings, such as resolution (the higher the resolution is, the larger number of contours can be detected for the shot) as well as amount of space which the volcano takes in the image (camera zoom).

3 Thermal Anomaly Detection Algorithm

The methods and approaches based on the contour detection are not applicable for thermal anomalies detection on night shots (taken by IR-cut equipped cameras) because of noise presence. Besides, the geometric form of such anomalies varies greatly from shot to shot and cannot be compared with some previously selected reference. Moreover, there could be bright spots in the image that are not related to volcano (moonlight, industrial objects light, etc.). Due to this, a special thermal anomaly detection algorithm for night images is developed.

The anomaly is interpreted as a part of a shot which brightness is higher than the brightness of the surrounding area and fades from the center to edges (Fig. 5). Such areas can correspond to possible signs of the volcano activity (for example, lava outflows from the craters).

The algorithm uses of a multi-scale DoG (Difference of Gaussian) detector [14]. It first finds the maximum points in DoG layers to locate anomaly centers. After that, it calculates the anomaly areas around each highlighted center. To do this, a breadth-first search of neighboring pixels is conducted given that the brightness value is not less than 0.1 of the central value. Because of the noise in the shots some highlighted areas can be identified as several different anomalies what produced incorrect results. That is why if the absolute brightness values for the centers of adjacent areas differ not more than 0.1, such areas are combined and considered as one.

For each anomaly found an attribute vector is calculated: the value of the DoG function in the center, anomaly elongation, the ration between a perimeter and a smallest possible perimeter (edge complexity), asymmetry of edge values, the difference between center brightness value and border brightness average value, the central brightness value and the number of a broad-scale layer where the given anomaly was found. At the final stage, the previously obtained data set is divided into classes: “thermal anomaly”, “false anomaly”, using the SVM-classifier [15] and a radial basis function [16], A average image analysis time is about 5 s. The paper [17] contains detailed algorithm description.

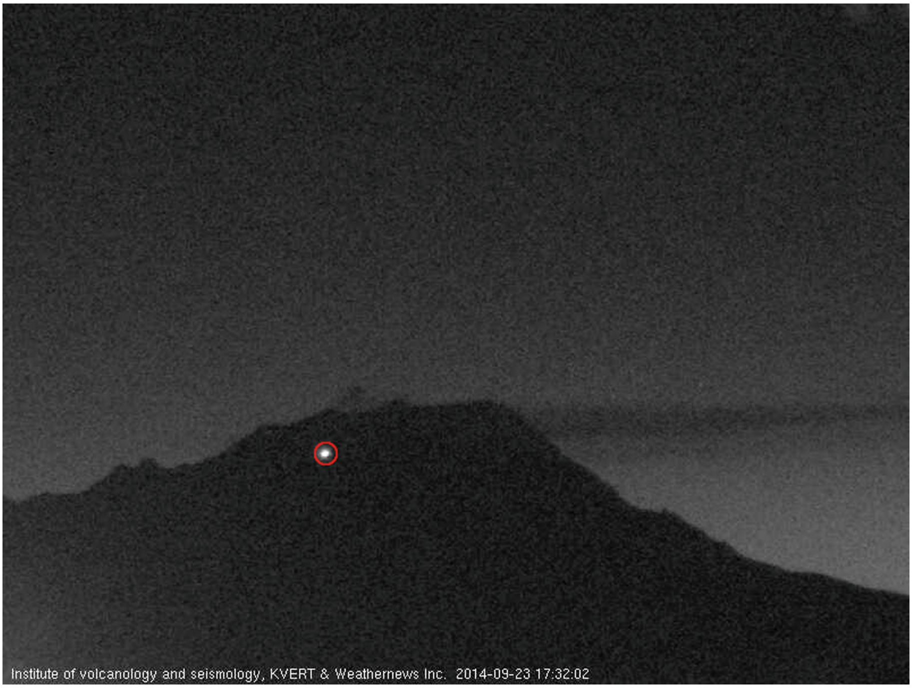


Fig. 5. Thermal anomaly example for Sheveluch volcano night image.

The tests of the suggested method were performed on a labeled training set of Sheveluch volcano night images produced by the Axis P1343 camera, with total amount of 5068 images. The 2% of images were classified incorrectly.

4 Image Processing Tools

To conduct the automatic analysis of the volcano images using the tools suggested, a special set of software tools was developed. Its operation diagram is shown in Fig. 6. At the first stage, the image is classified to be day or night shot, by comparing the pixel values in three channels (R, G, B): for night shots (grayscale) they will be the same, and for day shot – will not. After defining the shot type, the corresponding analysis algorithm is applied (Sect. 2 and 3), and the obtained results are presented. Program output has JSON format. For day shots, both contours visibility estimation and frequency characteristics are populated, as well as result estimate. This metadata is used for flexible search through the image archive and allows to reduce whole image flow to most informative dataset (Fig. 7).

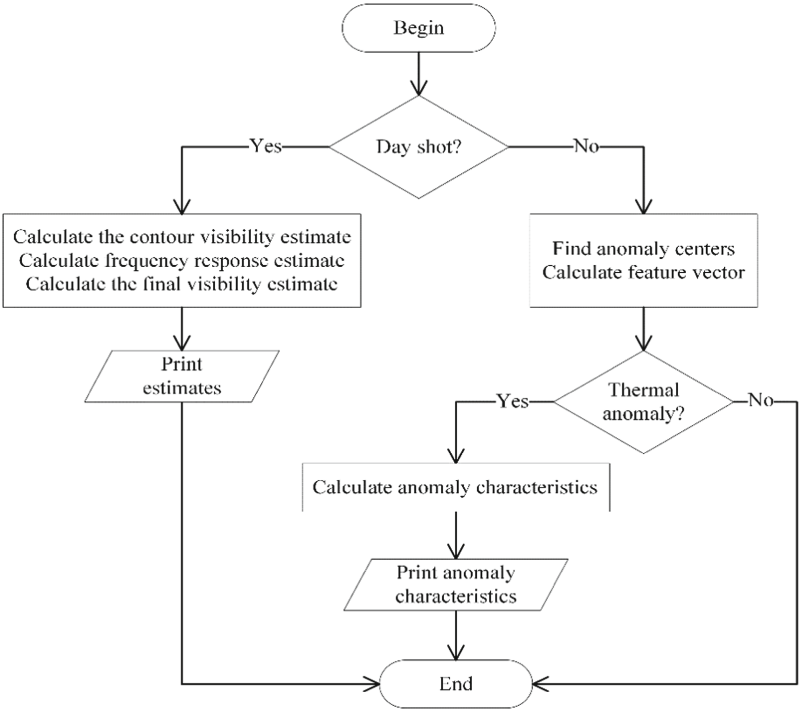


Fig. 6. Operation of the algorithm of volcano shot analysis.

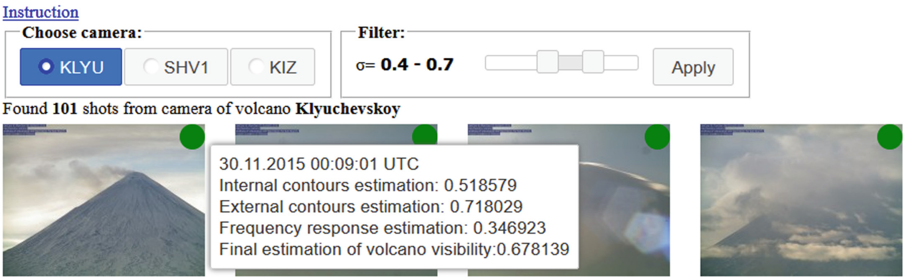


Fig. 7. Expert user interface to browse images classified by volcano visibility.

Data output for day shots (Fig. 8):

{“result”:0.72963, “contours”:0.72963, “frequency”:1}

Fig. 8. Klyuchevskoy volcano 21.02.2016 00:19 UTC.

The following values are calculated for thermal anomalies detected on night shots: size in pixels, average and standard deviations of the area brightness and center brightness value. These values help to search appropriate images in the archive and then to track changing in time the intensity of the possible anomaly and thus to define volcano state. The program output for night shot processing is as follows (Fig. 9):

{“night”:[{“data”:{“size”:209,
”mean”:0.626231,”sd”:0.174559,”maximum_value”:1}}]}

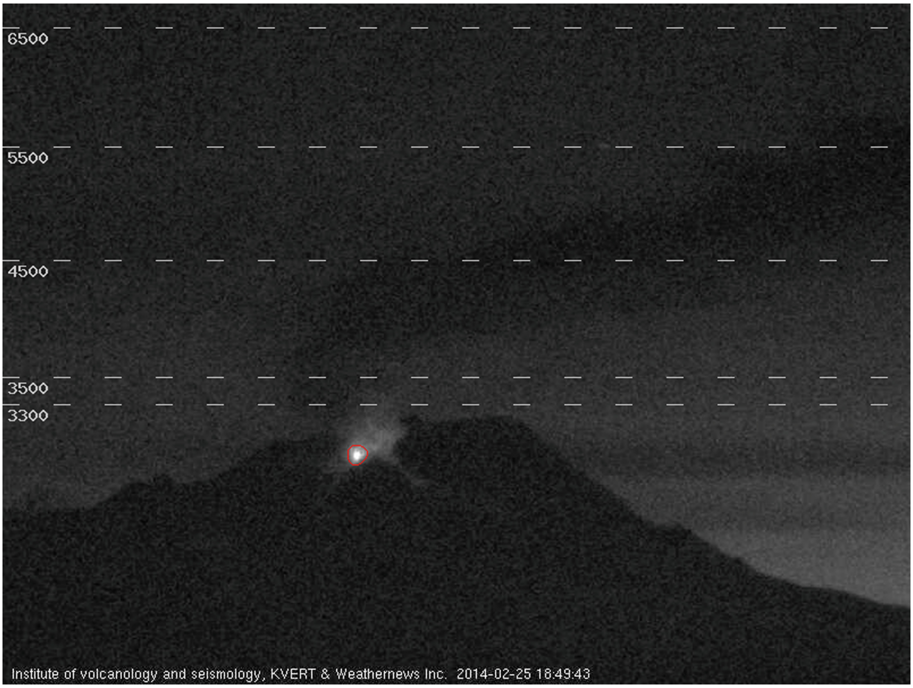


Fig. 9. A night shot of Sheveluch volcano 25.02.2014 18:49 UTC with the detected thermal anomaly.

5 Conclusion

The developed parametric methods and algorithms for volcano shots analysis allow to pre-filter large image flow by elimination of non-informative images and help to detect a possible volcano activity. However, their use in the automated system requires manual parameter setting and unique control for each video camera in the observation network. Therefore, the next work proposes the transition to more adaptive methods of image analysis, such as convolution neural nets, which are widely used today.

Using the possibilities of the developed tools, the accumulated historical archive of the images of Kamchatka volcanoes [9] are being processed (17 million shots). This will make it possible to produce a labelled dataset with various classes of shots and various volcano state captured. Thus, the obtained training dataset makes up the basis for the next work stage including:

- approbation of algorithms for unsupervised clustering of photo images based upon the analysis of the original images with deep neural nets – autoencoders;
- training of a convolution neural net for automatic classification of new volcano images.

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References

1. Girina, O.A., Gordeev, E.I.: KVERT project: reduction of volcanic hazards for aviation from explosive eruptions of Kamchatka and Northern Kuriles volcanoes. Vestnik FEB RAS **132** (2), 100–109 (2007)
2. Gordeev, E.I., Girina, O.A., Loupian E.A., Sorokin, A.A., Kramareva, L.S., Efremov, V.Yu., Kashnitskii, A.V., Uvarov, I.A., Burtsev, M.A., Romanova, I.M., Melnikov, D.V., Manevich, A.G., Korolev, S.P., Verkhoturov, A.L.: The VolSatView information system for monitoring the volcanic activity in Kamchatka and on the Kuril Islands. J. Volcanol. Seismolog. **10**(6), 382–394 (2016). https://doi.org/10.1134/S074204631606004X
3. Sorokin, A.A., Korolev, S.P., Malkovsky, S.I.: The signal automated information system: research and operational monitoring of dangerous natural phenomena in the Russian Far East. Sovremennye Problemy Distantsionnogo Zondirovaniya Zemli iz Kosmosa **16**(3), 238–248 (2019). https://doi.org/10.21046/2070-7401-2019-16-3-238-248
4. Malkovsky, S.I., Sorokin, A.A., Girina, O.A.: Development of an information system for numerical modelling of the propagation of volcanic ash from Kamchatka and Kuril volcanoes. Comput. Technol. **24**(6), 79–89 (2019). https://doi.org/10.25743/ICT.2019.24.6.010
5. Ando, B., Pecora, E.: An advanced video-based system for monitoring active volcanoes. Comput. Geosci. **32**(1), 85–91 (2006). https://doi.org/10.1016/j.cageo.2005.05.004
6. Viteri, F., Barrera, K., Cruz, C., Mendoza, D.: Using computer vision techniques to generate embedded systems for monitoring volcanoes in Ecuador with trajectory determination. J. Eng. Appl. Sci. **13**(3), 3164–3168 (2018). https://doi.org/10.3923/jeasci.2018.3164.3168
7. Rabal, H.J., Braga, J.R.A.: Dynamic Laser Speckle and Applications. CRC Press, Boca Raton (2009)
8. Kramareva, L.S., Andreev, A.I., Bloshchinskiy, V.D., Kuchma, M.O., Davidenko, A.N., Pustatintsev, I.N., Shamilova, Y.A., Kholodov, E.I., Korolev, S.P.: The use of neural networks in hydrometeorology problems. Comput. Technol. **24**(6), 50–59 (2019). https://doi.org/10.25743/ICT.2019.24.6.007
9. Sorokin, A., Korolev, S., Romanova, I., Girina, O., Urmanov, I.: The Kamchatka volcano video monitoring system. In: Proceedings of 2016 6th International Workshop on Computer Science and Engineering (WCSE 2016), pp. 734–737. The Science and Engineering Institute, LA, CA, USA (2016)
10. Kamaev, A.N., Urmanov, I.P., Sorokin, A.A., Karmanov, D.A., Korolev, S.P.: Images analysis for automatic volcano visibility estimation. Comput. Opt. **42**(1), 128–140 (2018). https://doi.org/10.18287/2412-6179-2018-42-1-128-140. (in Russian)
11. Canny, J.: A computational approach to edge detection. IEEE Trans. Pattern Anal. Mach. Intell. **8**(6), 679–698 (1986)
12. Urmanov, I., Kamaev, A., Sorokin, A.: Computer methods of image processing of volcanoes. In: Proceedings of the IV International Research Conference "Information Technologies in Science, Management, Social Sphere and Medicine" (ITSMSSM 2017), vol. 72, pp. 371–374. Atlantis Press, Paris (2017). https://doi.org/10.2991/itsmssm-17.2017.77
13. Borgefors, G.: Distance transformations in digital images. CVGIP **34**(3), 344–371 (1986). https://doi.org/10.1016/S0734-189X(86)80047-0

14. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vision **60**(2), 91–110 (2004). https://doi.org/10.1023/B:VISI.0000029664.99615.94
15. Shmilovici, A.: Support vector machines. In: Data Mining and Knowledge Discovery Handbook. Springer, Boston (2009). https://doi.org/10.1007/0-387-25465-X_12
16. Schölkopf, B., Tsuda, K., Vert, J.P.: Kernel Methods in Computational Biology. MIT Press, Cambridge (2004)
17. Kamaev, A.N., Korolev, S.P., Sorokin, A.A., Urmanov, I.P.: Detection of thermal anomalies in the images of volcanoes taken at night. J. Comput. Syst. Sci. Int. **59**(1), 95–104 (2019). https://doi.org/10.1134/S106423071906008X