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THE CONCEPT OF A SOFTWARE AND HARDWARE COMPLEX FOR EARLY DETECTION OF FOREST FIRES

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Annotation: *This paper describes conceptual solution of software and hardware complex for early detection of forest fires based on Machine Vision and algorithms of image processing. the urgency of this work is a difficult situation in the field of combating such technological disasters as forest fires. This paper based on research of already existing platforms and systems. Problem of forest fires is one of the most significant problems of human race, interfaced with problems of ecology, politics and economics. One of the most effective methods of fighting fires is their earlier detection and stopping at the initial stages until the conflagration has become spontaneous nature*

Key words: *early detection of forest fires, software and hardware complex, image processing algorithms, Python, Open CV, machine vision, methods of dealing with technological disasters*

КОНЦЕПТ ПРОГРАММНО-АППАРАТНОГО КОМПЛЕКСА ДЛЯ РАННЕГО ОБНАРУЖЕНИЯ ЛЕСНЫХ ПОЖАРОВ

Аннотация: *В данной статье описывается концептуальное решение программно-аппаратного комплекса для раннего обнаружения лесных пожаров на основе Machine Vision и алгоритмов обработки изображений. Актуальность данной работы представляет собой сложную ситуацию в области борьбы с такими техногенными катастрофами как лесные пожары. Эта статья основана на исследовании уже существующих платформ и систем. Проблема лесных пожаров является одной из наиболее значительных проблем человеческой расы, связанной с проблемами экологии, политики и экономики. Одним из наиболее эффективных методов борьбы с пожарами является их раннее обнаружение и прекращение на начальных этапах, пока пожар не приобрел стихийный характер.*

Ключевые слова: *раннее обнаружение лесных пожаров, программно-аппаратный комплекс, алгоритмы обработки изображений, Python, Open CV, машинное зрение, методы борьбы с техногенными катастрофами*

ОРМАН ӨРТТЕРІН ЕРТЕ СӨНДІРУГЕ АРНАЛҒАН БАҒДАРЛАМАЛЫҚ-АППАРАТТЫҚ КЕШЕН ТҮСІНІГІ

Аңдатпа: *Бұл мақалада Machine Vision және кескін өңдеу алгоритмдері негізінде Орман өрттерін ерте анықтауға арналған аппараттық-бағдарламалық кешеннің тұжырымдамалық шешімі сипатталған. Аталған жұмыстың өзектілігі – орман өрттерін ерте айқындауға технологиялық апаттармен күрес саласындағы қиын жағдай. Еңбекте қолданыстағы платформалар мен жүйелерді зерттеуге негізделген. Орман өрттері – адамзат баласының маңызды мәселелерінің бірі. Өрт сөндірудің тиімді әдістерінің бірі өрттің стихиялық сипат алғанға дейін оларды бастапқы кезеңдерінде анықтау, байқау және тоқтату.*

Түйінді сөздер: *орман өрттерін ерте анықтау, бағдарламалық-аппараттық кешен, кескіндерді өңдеу алгоритмдері, Python, Open CV, машиналық көру, технологиялық апаттармен күрес әдістері*

Introduction

It is hard to imagine the life of a modern person without the use of fire. Thanks to him, people live in comfortable conditions – in warm homes, lighted rooms, eat delicious food, and daily use items created with the flame. The process of obtaining and subjugating the fire was very complex and lengthy. Thanks to the ancient man, we can use this resource. However, an open flame going out of control turns into a real natural disaster. Forest fire – this is the uncontrolled spread of fire in the forest. In any situation, even a small fire can develop into a natural disaster. Currently, the probability of fire and large-scale spread of fire due to natural factors does not exceed 20%. Most forest fires are triggered by human activities. Forests are an integral part of the natural balance in which people live. Typically, such disasters are observed only when they have already spread to a large area. The result is devastating losses and irreparable damage to the environment and atmosphere. The problem is that forests are usually remote, abandoned, and uninhabited areas filled with trees, shrubs, deadwood, and wilted grass with dry leaves, etc., which are a potential zone possible fire. A small piece of glass in sunny and hot weather, acting as a lens, is enough to ignite dry wood, foliage, or wilted grass. As soon as the fire begins, combustible materials contribute to the strengthening of the flame and its faster spread. The initial ignition stage is usually called the "surface fire" stage. At this stage, an increase in flame intensity occurs. It is at this moment that the fire goes into the category of uncontrollable ones, and the damage that may occur depends directly on weather conditions and other factors, which makes it almost impossible to make a preliminary assessment. To prevent such scenarios, it is necessary to carry out several measures to prevent, early detection and preliminarily work with potentially dangerous areas.

Solution concept

The solution may be to create an integrated, but a modular system. An integrated approach to the early detection and prevention of forest fires is based on a combination of different detection systems depending on the probability of forest fires, the size of the territory and the presence of a person associated with an adequate logistics infrastructure, training, simulation results and innovative fire fighting technology. A key factor in fighting forest fires is timely detection. To avoid the uncontrolled widespread occurrence of forest fires, it is necessary to detect fires in the first stages and to prevent their spread. It is important to move fire fighting equipment and qualified personnel directly to the fire source as soon as possible. Adequate material and technical infrastructure are urgently needed to provide a sufficient amount of fire fighting and maintenance equipment. An equally important factor is constant monitoring. Also, staff training is an important component of the successful management of forest fires. An integrated approach to the detection and suppression of forest fires is based on a combination of different detection systems depending on the risks of fires, the size of the territory and the presence of a person, consisting of all the necessary parts, such as early detection, remote sensing methods, logistics and training using simulators and training models. The sounding methods used are determined by different degrees of risk of natural fire, the size of the region, and the availability of human resources. Local staff is involved in monitoring small areas at high risk. For areas of very high and low risk, satellite and aero control are possible. Video and photo material in broadcast mode is transmitted to control centers and analyzed to identify risks and build models to combat them. If the fire identified and evaluated, the fire will be triggered by an alarm that goes directly to the fire department.

Airship and drones based early forest fire verification platform

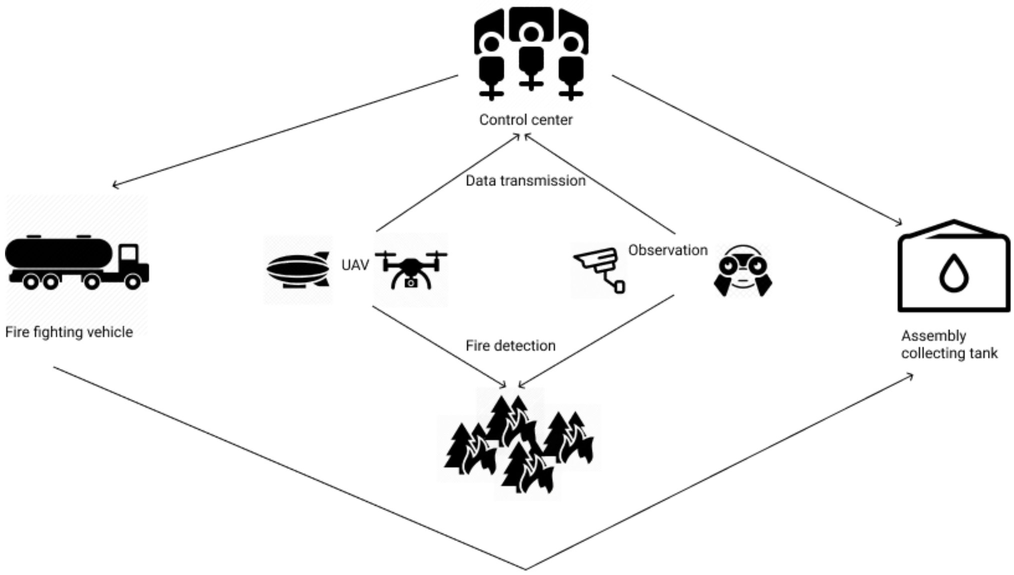

Figure 1. Schematic structure of the integrated forest fire detection and fire fighting system

One of the alternative sources of fire monitoring can be through a radiometer, gas and smoke detectors, and a heat chamber attached to the airship. The advantage of an airship with a length of 9 meters and a diameter of 2.3 m is its high load capacity. Management, communication, and data transmission take place through the middle of a computer mounted on an airship. The ground station consists of a user interface for transmitting and receiving flight data from the airship. Users request data via TCP/IP at the ground station. The resulting data is combined with GPS airship data and time stamps for visualization.

The platform for the early detection of fires can serve as pilot drones or drones on the remote control. One existing solution is the AirRobot AR100-B. This platform offers a low-cost alternative to manned helicopter aerial surveillance. The drone allows the fire brigade to have up-to-date information on the situation and incidents during the entire mission. It can be used both to confirm the alarm detected by the video system and for reconnaissance, helping the operator find hot spots.

The diameter of the drone does not exceed one meter, with a weight of not more than 1 kilogram. The flight time is about 25 minutes, depending on the weight of the carried cargo. The maximum speed of the AR100-B is 10m/s (36 km/h), the maximum wind load is 8 m/s (28.8 km/h). Operation does not require flying experience and special qualifications. If necessary, you can ensure uninterrupted transmission of information in real time by connecting the appropriate modules. Modules

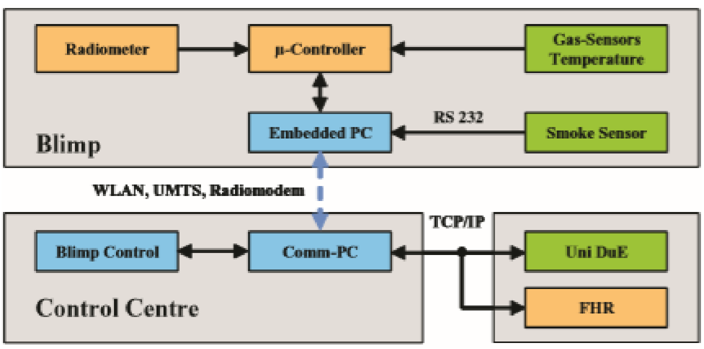

Figure 2. Communication structure

Figure 3. AirRobot AR100-B drone

may vary depending on the task and the specifics of the marsness on which they are planned to operate. Telemetry data is displayed in real time at the ground station and can be tracked on a map throughout the flight. All processing for the detection of obstacles, as well as the prevention of stagnation, will occur offline without operator intervention.

Sensors based early forest fire verification platform

If it is necessary to confirm a possible fire, with insufficient information from the video/photo, there is a need to use sensors. Therefore, the sensors must be largely immune to interference, such as steam, fog, dust pollution, and water condensation. Detectors analyze incoming air samples by analyzing them. Early forest fire detection sensors must meet many specific requirements compared to conventional applications. High sensitivity is necessary to detect even low concentrations of smoke; dilution and strong turbulence caused by the wind are significant factors. Due to the high hydrogen content during an open fire, an H2 sensor [0 – 10 ppm] was used. The main features of this semiconductor gas sensor (GTE GSME) are its very fast response time and high sensitivity. The CXHX sensor [0-5ppm] is used because hydrocarbon sensors are sensitive to organic fire products. Rapid temperature fluctuations are measured by a temperature sensor. Also, a highly sensitive suction system (Hekatron ASD535) is used to detect smoke when observing an extinguished fire with an airship. Thus, a distinction can be made between gas emissions in a fire extinguished and even low smoke concentrations in a fire. In addition to these sensors, the airship is equipped with a microwave radiometer and a camera.

Surveillance cameras based early forest fire verification platform

The mentioned above methods for detecting a forest fire include the possibility of using surveillance cameras. One of these methods is the technology based on the accumulation of the image in the foreground in a compartment with an optical stream. Images are calculated from foreground images, which are processed using frame difference methods. To distinguish flame images from smoke, two parameters are used. Areas containing fire are recognized by a model built on the principle of accumulating foreground frames during the calculation of the optical flux. The model also uses an algorithm for recognizing moving objects to recognize puffs of smoke. Due to this, the application of the algorithm is possible in the following cases:

- fire with flame and without smoke
- fire with smoke and without flame
- fire with flame and smoke.

Compared to conventional fire detectors, a system built on a video series has advantages such as the speed of response to a threat, range of flame detection, wider coverage of the territory, etc. Among other things, such systems can also be used for monitoring large areas of forest with complex terrain. But most of the methods based on video fire detection have high rates of false alarms. Most detecting methods based on the visual features of fire flame or smoke including color, textures, geometry, flickering, and motion. It is possible to determine the appearance of ignition based on color to segment flame regions, as was done by Yamagishi and Yamaguchi [1, 2], Celik et al. [3], Chen [4]. Liu and Ahaja [5] and Yuan et al. [6] used an algorithm based on the analysis of Fourier coefficients for flame circuits to fix the fact of ignition. Ugur et al. [7] and Dedeoglu et al. [8] in their writings suggested temporal and spatial wavelet method which used for fire analysis. In the current conditions, the trend of the development of early fire detection methods to combat forest fires is clearly visible. What contributes to increased interest in this issue.

Generally, the flames usually display red shade colors, which could be used in a model for flame detecting. Unfortunately, some fire-like regions in an image may have the same colors like fire. So these fire-similar areas are usually extracted as the real fire from an image. There are two possible causes of such false alarms:

- non-fire objects with same colors as real flame

- background illumination of fire-like sources of light

In both cases, the extraction of fire-flames becomes complex and unreliable. The most important aspect to distinguishing between real fire or smoke and flame or smoke colored objects in their movement nature. So, it usually using color and motion features for creating burning fire validating methods. Such fire dynamic features include random movements of flames, growing rate, oscillation, and flame different shapes. According to turbulent nature, smoke and fire have and chaotic nature. If the contours of an object represent chaotic varying behavior, then this is a sign of the presence of flame or smoke on the video frame.

The moving pixels of the images could be determined by using a frame differential method, where (*x*, *y*) represents the coordinates of the pixels that are formulated with a long direction as the x-axis and the other direction as the *y*-axis. *I*(*x*, *y*,*k*) represents the pixel values of (*x*, *y*) in the current frame. *I*(*x*, *y*,*k* 1) represents the pixel values of (*x*, *y*) in the previous frame. *L* is the threshold. Equation represented in the figure below:

$$FD(x,y,k) = \begin{cases} 1 & if|I(x,y,k) - I(x,y,k-1)| > L \\ 0 & otherwise \end{cases}$$

Figure 4. Moving pixels differential method

(i) $0 \leq H \leq 60°$
(ii) $0 \leq S \leq 0{,}2$
(iii) $127 \leq I \leq 255$

Figure 5. HIS sequence

Color model for smoke differs from flame one because smoke displays grey shades so he conditions R a G a B a and with I (intensity) component of HIS color model K1 ≤ I ≤ K2. The function of smoke recognition looks like[28]:

$$M = \max\{R(i, j),G(i, j), B(i, j)\}$$
$$N = \min\{R(i, j),G(i, j), B(i, j)\}$$
$$I = 1/3(R(i, j),G(i, j), B(i, j))$$

Figure 6. RGB HIS sequence

If the pixel FD (x, y, k) satisfies both the conditions object considered as a smoke pixel, otherwise FD (x, y, k) is not a smoke pixel. Approximately typical value ranges are 5 to 20 and light-gray and dark-gray smoke pixel threshold ranges from 80 to 150 and 190 to 255. The pixels that pass the color decision rule marked as smoke. Foreground images appear in the same regions during a consecutive time frame. For describing it could be used such equation, where Value b1 is the accumulation augmenter, value b2 is the accumulation attenuation[28]. Value b2 is set to 1 generally.

$$H_\tau(x,y,k) = \begin{cases} H_\tau(x,y,k-1) + b1 & if FD(x,y,k) = 1 \\ \max(0, H_\tau(x,y,k-1) - b2) & otherwise \end{cases}$$

Figure 7. Foreground accumulated pixels equation

The values of pixels that represent frames of foreground images detected in the same region during a time frame. Foreground accumulated images are the results from the stack of consecutive image frames, which alreday wheighted. Than the more times the same region of foreground images detected, the bigger of the pixels' values of the corresponding pixels in it. The pixel values will decrease if the corresponding region no longer appears in choosen region. According to experiments [28], results show that as the grads variation of color and brightness of flame is extremely bright. Every pixel value of flame changes, so the whole flame region in the images could be detected via frame differential method. If b1 and b2 are set 1, the value of H will increase soon.

Smoke nature looks like clouds with haotic movements and not changebal brightness of pixel in short period of time. There is are condition for accumulating foreground image of smoke is such: the parameters b1 and b2 can be set as b1> b2. Flame and smoke regions can also be separated. The next step is smoke region determination. Visible characteristics of smoke such as color and shades are less steep. So that smoke is harder to be differentiated. The pixels in the center of each smoke block are considered as feature points and do the optical flow calculation. It greatly decreases the algorithm computation complexity.

First of all accumulated images sequences with potential smoke on foreground should be divided to blocks. Then it needs to sum up the values of pixels within filtred blocks.

$$H(x,y,t) > T$$

Figure 8. Pixel sump up satisfying condition

Then find the center points coordinates of smoke blocks, flow vectors will be calculated according to rule bellow. The Pyramidal Lucas-Kanade feature optical flow vector looks like:

$$d_{opt} = G^{-1}\overline{b}$$

Where G is:

$$G = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$\overline{b} = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} \delta I \cdot I_x \\ \delta I \cdot I_y \end{bmatrix}$$

Figure 9. The Pyramidal Lucas-Kanade feature condition

This process could be updated via recursion to minimize complexity of calculations. Equation results fits to level L-1 bypassing the new start values. This procedure goes on until it rexahes the finest resolution.

$$\begin{aligned} I^L(x,y) = {} & \frac{1}{4} I^{L-1}(2x,2y) + \\ & \frac{1}{8}(I^{L-1}(2x-1,2y) + I^{L-1}(2x+1,2y) + I^{L-1}(2x,2y-1) + I^{L-1}(2x,2y+1)) + \\ & \frac{1}{16}(I^{L-1}(2x-1,2y-1) + I^{L-1}(2x+1,2y+1) + I^{L-1}(2x-1,2y+1) + I^{L-1}(2x+1,2y+1)) \end{aligned}$$

Then the Back-Propagation Neural Network can be used a for the smoke feature classification. In Richard and Lippmann [17], they presented the step of the back-propagation training algorithm. The output layer uses a log-sigmoid transfer function, so the outputs of the network are between 0 and 1.

$$f(x) = \frac{1}{1+e^{-cx}}$$

Figure 11. log-sigmoid transfer function

The next phase is flame recognition. Flame motion recognition method based on block image processing. The nature of flame is turbulent as smoke`s one. If there are no external factors, the regions of flame will be recurring at regular intervals in some areas. Flame flickering frequency is between 2 Hz and 12 Hz. Ordinary cameras with a rate of 25 frames per second capture at least one cycle movement of flickering per time. The foreground image using the differential frame method usually contains areas of flame. At certain time intervals T, the flame accumulates in the concrete areas. Each frame of video is divided into blocks with 8×8 resolution for extartction. Then the values of pixels within a block are summed up. All methods listed below represents supervised methods for fire detection, then let`s see on non-supervised group.

One of the remote sensing products is the Thermal Anomalies provided by NASA [29] [30]. This product improved by additional sensors such as Visible Infrared Imaging Radiometer Suite (VIIRS). In fact, this product providing information within three hours of the satellites overpass.The main goal are development algorithm to identify each fire, estimare it, and fire spread monitoring. Such method allows to focus on each fire case and minimizing the computational cost. Firstly alfgorithm creates clusters with anomalies. Each cluster is a potential fire. In order to avoid false positive clusters, they are filtered via the CORINNE Land Cover 2012 (CLC2012) [31]. After filtering, it needs to create an R-Tree. All R-trees with the CLC2012 have their geometries and should be checked for land covers types with a point-in-polygon procedure. The R-Tree is created only once and uses further. Algorithm based on rules from Scikit-Learn [32] Python library. As output results, algorithm provide set of labeled groups of anomalies. In next steps, burnt area is computed applying the alpha shape algorithm [33] for obtaining set of points. The alpha shape algorithm stops when a given set of points creates two different polygons. This stop condition based on the rule that each group should have only one burnt area. Finally, each fires have next points:

- a potential burnt area
- an extent of the fire
- percentage of area inside vegetated area
- initial date and time
- all the properties of the thermal anomalies associated with the fire.

Algorithm checks previous execution results, therefore, the clustering of the current execution adds the points of the previous burnt areas polygons and adds the new potentila areas. It aloow to detect such cases where some thermal anomalies can joint in a single fire. But, some fire cases are false positives. According to that, each fire shoul be checked for unusual fire behavior. For example, detections with rarely active or with a non constant activity during a long time should be labeled as potential false positives.

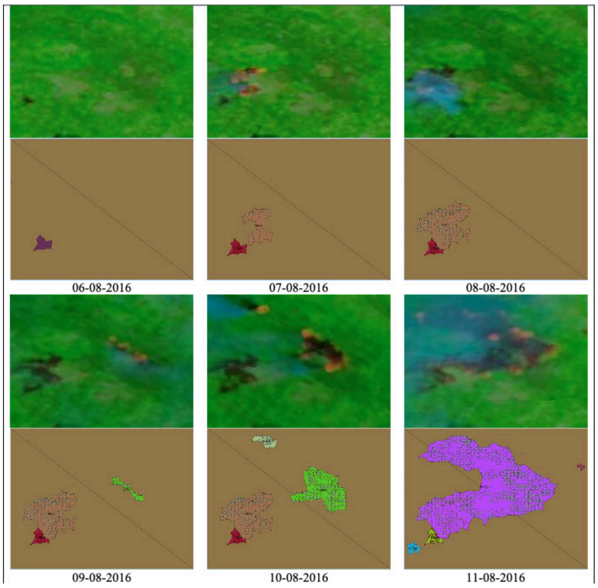

Figure 12. Algorithm maped case with joint fires

The algorithm do not provide that each cluster is single fire. However, it could be a reason for much more complex and costly calculations focused on the fire degree. It is important to use some additional method to increase burnt area estimation accuracy. The thermal anomalies is main factor for fire detection. Though, such solution has some limitations. Results of the experiment [34] show that this algorithm could not be used as a common method for burnt areas calculations. It could be applied as a fast mapping estimation tool for big fires. The reason is the spatial resolution of the thermal anomalies.

Conclusion

According to written below, they are a lot of different systems which uses for fighting with fire. Most of them based on early fire detection. This paper described at least three different solutions. Most of them based on the machine vision or processing of information from external sensors. These solutions show their effectivity in early fire detection but still have a high false alarm rate. It does not depend on the concrete

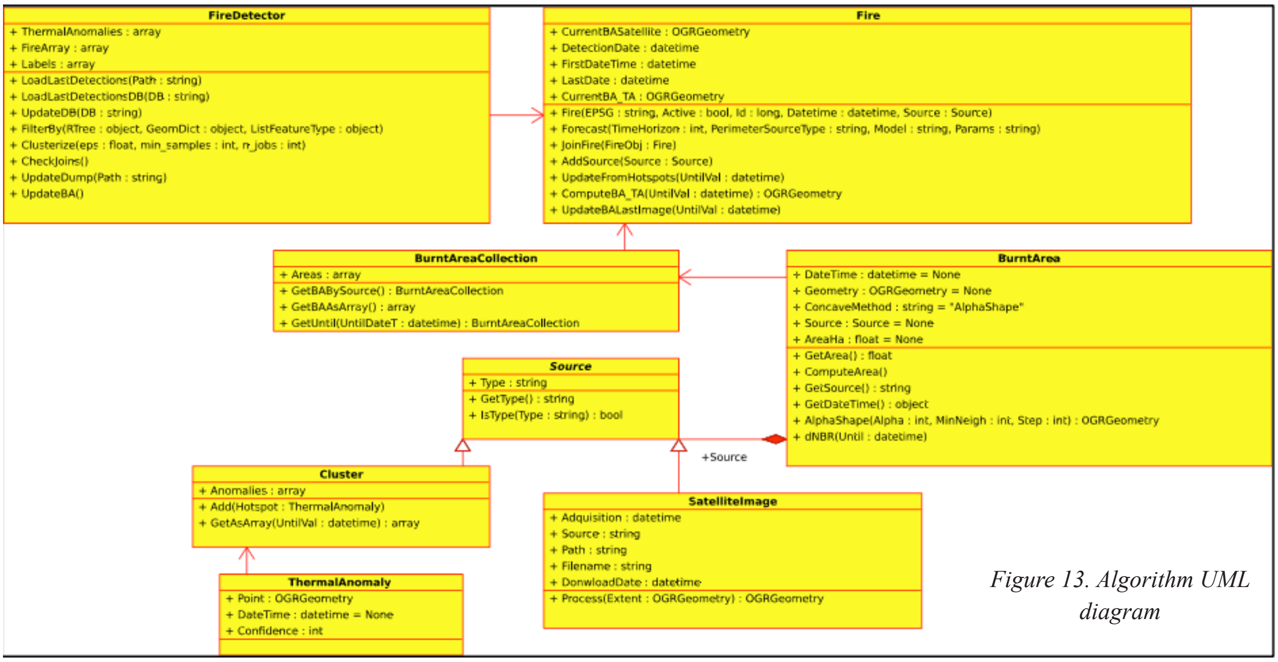

Figure 13. Algorithm UML diagram

algorithm, because the nature of flame and smoke is chaotic and it is really hard to determine it in some cases. But a combination of these methods allows to cope with high false rate results and increase systems productivity and stability. Most disturbances like fire-like color objects can be differentiated from flame via foreground accumulation image. The proposed method will be further improved in future work.

REFERENCES

1. Yamagishi H., Yamaguchi J., 1999. “Fire Flame Detection Algorithm Using a Color Camera,” Proceedings of 1999 International Symposium on Micromechatronics and Human Science, Nagoya, Japan, pp. 255-260.
2. Yamagishi H., Yamaguchi J., “A Contour Fluctuation data Processing Method for Fire Flame Detection Using a Color Camera”, IEEE 26th Annual Conference on IECON of the Industrial Electronics Society, Nagoya, Japan, pp. 824.
3. Celik T., Demirel H., Ozkaramanli H., 2006. “Automatic Fire Detection in Video Sequences”, Proceedings of European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September.
4. Chen T., Wu, P., Chiou Y., 2004. “An Early Fire-Detection Method Based on Image Processing,” Proceedings of IEEE ICIP ’04, pp. 1707–1710.
5. Liu C.B., Ahuja N., 2004. “Vision Based Fire Detection,” In: Proceedings of ICPR 2004. Proceedings of the 17th International Conference on. 4, pp.
6. Yuan F.N.,, Liao G.X., Zhang Y.M., et al., 2006. Feature Extraction for Computer Vision Based Fire Detection, Journal of University of Science and Technology of China 36, p. 39.
7. Ugur T.B., Dedeoglu Y., et al., 2006. Computer Vision Based Method for Real-time Fire and Flame Detection, Pattern Recognition Letters 27, p.49.
8. Dedeoglu N., Toreyin B.U., et al., 2005. “Real-time Fire and Flame Detection in Video,” Proceedings of IEEE 30th International Conference on Acoustics, Speech, and Signal Processing (ICASSP’05). Philadelphia, PA, USA. 2005.2(2), pp. 669-672.

9. Xiong Z.Y., Caballero R., Wang H.C., Alan M., Finn Muhidin A.L., Peng, P.Y., 2007. Video-based Smoke Detection: Possibilities, Techniques, and Challenges, IFPA, Fire Suppression and Detection Research and Applications - A Technical Working Conference (SUPDET), Orlando, FL.
10. Yuan F.N., 2008. A Fast Accumulative Motion Orientation Model Based on Integral Image for Video Smoke Detection, Pattern Recognition Letters 29, p. 925.
11. Ugur T.B., Dedeoglu Y., Cetin A.E., 2005. "Wavelet Based Real-time Smoke Detection in Video," 13th European Signal Process Conf. EUSIPCO2005, Antalya, Turkey.
12. Ho C.C., 2009. Machine Vision Based Real-time Early Flame and Smoke Detection. Measurement Science and Technology 20, No.4.
13. Celik T., Demirel H., Ozkaramanli H., 2006. "Automatic Fire Detection in Video Sequences," Proceedings of European Signal Processing Conference (EUSIPCO 2006), Florence, Italy, September 2006.
14. Collins R., Lipton A., Kanade T., et al., 2000. A System for Video Surveillance and Monitoring. Tech. Report CMU-R1-TR-00-12, Robotics Institute, Carnegie Mellon University, 2000.
15. Yu C.Y., Zhang Y.M., 2009. "Texture Analysis of Smoke for Real-time Fire Detection," IEEE Second International Workshop on Computer Science and Engineering. 2009, Qingdao.
16. Barron J.L., Fleet D.J., Beauchemin S., 1994. Performance of Optical Flow Techniques, International Journal of Computer Vision 12, p. 43.
17. Richard P., Lippmann, 1987. An Introduction to Computing with Neural Network, IEEE ASSP Magazine, p. 4.
18. von Wahl N., Heinen S., Tobera R., Nüßler D., Brauns R., Schröder M., Knott P., Krüll W., and Willms I., 2009. Intermediate Report Internationale Waldbrandbekämpfung iWBB, FHR-Report Nr. 134, FGAN Research Institute for High Frequency Physics and Radar Techniques, Wachtberg, Germany.
19. Henrichs M., 2009. Armored and Tracked Vehicle for Rescue/Extinguish/Defend Missions, 14th International Conference on Automatic Fire Detection, AUBE '09, Duisburg, Germany.
20. AirRobot GmbH & Co. KG, http://www.airrobot.de
21. GTE Industrieelektronik GmbH, http://www.adicos.de
22. Krüll W., Willms I., Tobera R., and Wiggerich B., 2009. Early forest fire detection and suppression - an integrated approach, 14th International Conference on Automatic Fire Detection, AUBE '09, Duisburg, Germany.
23. Tobera R., Krüll W., and Willms I., 2009. Optical smoke and gas sensors as an additional method for early wildfire verification, 14th International Conference on Automatic Fire Detection, AUBE '09, Duisburg, Germany.
24. Hekatron Vertriebs GmbH, http://www.hekatron.de
25. Krüll W., Tobera R., Willms I., von Wahl N., Heinen S., 2008. An integrated approach for early forest fire detection and suppression, First International Conference on Remote Sensing Techniques in Disaster Management and Emergency Response in the Mediterranean Region, Zadar, Croatia.
26. von Wahl N., Heinen S., 2009. Advantages of millimeter waves in fire detection and monitoring, 14th International Conference on Automatic Fire Detection, AUBE '09, Duisburg, Germany.
27. Nüßler D., Essen H., von Wahl N., Zimmermann R. Rötzel S., and Willms I., 2008. Millimeter Wave Propagation through dust, SPIE conference proceedings.
28. Chunyu Yu, Zhibin Mei, Xi Zhang, 2013. A real-time video fire flame and smoke detection algorithm, The 9th Asia-Oceania Symposium on Fire Science and Technology

29. I.A. Csiszar, J.T. Morisette and L. Giglio, "Validation of active fire detection from moderate-resolution satellite sensors: the MODIS example in northern Eurasia," IEEE Transactions on Geoscience and Remote Sensing, vol. 44, pp. 1757-1764, 2006.
30. W. Schroeder, P. Oliva, L. Giglio and I.A. Csiszar, "The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment," Remote Sensing of Environment, vol. 143, pp. 85-96, 2014.
31. C.L. Cover, "Corine Land Cover," European Environment Agency, Copenhagen, 2000.
32. F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg and others, "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825-2830, 2011.
33. N. Chiaraviglio, T. Artés, R. Bocca, J. López, A. Gentile, J.S. M. Ayanz, A. Cortés and T. Margalef, "Automatic fire perimeter determination using MODIS hotspots information," in e-Science (e-Science), 2016 IEEE 12th International Conference on, 2016.
34. Tomàs Artés, Roberto Boca, Giorgio Liberta, Jesús San-Miguel, "Non- supervised method for early forest fire detection and rapid mapping," Proc. SPIE 10444, Fifth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2017), 104440R (6 September 2017); doi: 10.1117/12.2280714