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ANALYSIS OF METHODS FOR REDUCING THE NUMBER OF FALSE ALARMS IN VIDEO-BASED FIRE DETECTION SYSTEMS

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Abstract – The article focuses on a review and analysis of methods for reducing false alarms in video-based fire detection systems (VBFDS). The author of the article has designed a neural network and video-based flame detection algorithm to evaluate the effectiveness of methods found in the literature and other sources. The video-based flame detection algorithm was designed using a CIFAR-10-NET convolutional neural network. The D-Fire database, which contains 50000 fire images, was used to learn and test the algorithm. An error matrix was used to determine the effectiveness of the algorithm and methods to reduce the number of false alarms in video-based fire detection systems to determine parameters such as sensitivity (True Positive Rate, TPR), precision (Positive Predictive Value, PPV) and accuracy (ACC).

Key words – false alarms, fire protection systems, neural networks, video-based fire detection

INTRODUCTION

The method of video-based fire detection relies on the use of features ignored in classical Fire Alarm Systems (FAS) such as colour, shape or movement of flame and smoke[1]. VBFDS operation is most often based on machine learning or neural network techniques[2]. An algorithm based on these techniques processes and analyses the image to extract the desired features based on which flame detection is performed.

A flame is a dynamic phenomenon. Its features such as shape, colour or flicker frequency can change significantly over a short period of time[3]. In addition, changing environmental conditions such as atmospheric conditions or the material being burned also affect flame characteristics. Due to the high dynamics of changes in flame characteristics, VBFDSs still have a high false alarm rate compared to classic FASs[4].

1 ANALYSED METHODS FOR REDUCING THE NUMBER OF FALSE ALARMS IN VBFDSS

The problem of false alarms in VBFDSs has been addressed in numerous articles in this field. The authors of [5] noted that most VBFDSs algorithms are based on the Support-Vector Machine (SVM) classifier. According to the authors, in order to improve the efficiency of the algorithm, they proposed replacing the SVM classifier, with the NB (Naive Bayers) classifier. The NB classifier in theory requires less learning data, and is more accurate in extracting features that are related to the fire itself.

The authors of [6] propose the use of the Tracking Growth Object (TGO) to increase the effectiveness of VBFDS. Fire is a phenomenon that does not change its position in space, while it can spread. The use of TGO instead of classical motion detection will reduce the number of false alarms caused by phenomena that have some characteristics of fires, but are not them, such as car lights. In detection, the ROI (Region of Interest) of a frame is extracted and analysed according to equation (1)[6]:

$$FP = F(P(s))_{i+1} - F(P(s))_i \tag{1}$$

The symbol F stands for image and P(s) for the number of pixels of the flame. With this equation, the algorithm is able to determine whether an object in a given ROI is a flame that is starting to spread.

The last method is colour filtering[7]. It involves a preliminary analysis of images before they are subjected to a classification process by the algorithm. Depending on the colour space description model used, ranges of pixel values that will be retained in the image are determined, while the remaining pixels whose value is not within the designated ranges will be rejected by this filter. In this study, the Hue Saturation Value (HSV) model was used.

2 VIDEO-BASED FIRE DETECTION ALGORITHM

In order to test the effectiveness of false alarm reduction methods, a proprietary flame detection video algorithm was developed. The algorithm was developed based on an existing CIFAR-10-NET convolutional neural network with an SVM classifier. The neural network was learned using the Transfer Learning (TL) method, which allows the algorithm to be learned correctly using less learning data. When learning with the TL method, only the last layers of the neural network are changed, which significantly reduces the time required to learn such a network.

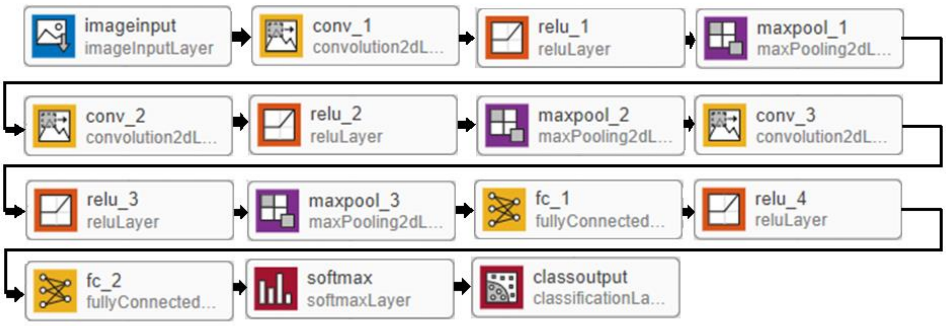

Fig. 1. Structure of neural network layers.

A stochastic gradient descent with momentum (SGDM) was used to learn the original version of the neural network. The method used differs from other gradient methods in that calculations in each step are performed on only one observation, rather than on the entire set, which makes it possible to reduce the use of computing power and speed up the learning process. The disadvantage of this method is the possibility of not finding the minimum of the function, but this is not necessary, since from the point of view of machine learning techniques a value close to zero is sufficient. The use of so-called momentum reduces the chances of the algorithm getting stuck in a local minimum during the calculation.

The workstation on which the learning process was performed has 16 GB of RAM and a Windows 10 operating system.

The process of learning the basic version of the network took 30 cycles (one cycle is one complete pass of the algorithm over the learning dataset). The process took approximately 120 minutes. The learning data was 5000 images representing a fire.

The study used the public database D-Fire[7], which contains more than 20000 images of fire. 1000 images with fire and 1000 without fire were drawn. The algorithm signals fire detection when the probability of correct flame detection is 98%. Correct detection was defined as the detection of a flame and the correct indication of its position in the image.

3 FINDINGS

Table 1 shows the results of tests conducted on a basic version of the network, i.e. without the previously discussed methods of reducing false alarms in SWDP implemented. The results are presented in the form of an error matrix to determine the sensitivity, precision and accuracy of the algorithm. Images where the algorithm correctly detected the flame were classified as TP (True Positive). Cases where the algorithm failed to detect the flame because the image did not contain a fire were classified as TN (True Negative). Images that contained a flame and it was not detected by the algorithm were classified as FN (False Negative). Cases where the image did not contain a fire and the algorithm signalled detection were marked as FP (False Positive). The calculations of the TPR, PPV and ACC indicators are expressions from (2) to (4).

Table 1. Test results of the basic version of the neural network

TP	TN	FN	FP
697	856	303	144

$$TPR = \frac{TP}{TP+FN} = \frac{697}{697+303} = 0{,}697 \tag{2}$$

$$PPV = \frac{TP}{TP+FP} = \frac{697}{697+144} = 0{,}829 \tag{3}$$

$$ACC = \frac{TP+TN}{TP+FN+FP+TN} = \frac{1553}{2000} = 0{,}777 \tag{4}$$

Table 2 shows the results of tests with implemented methods for reducing false alarms. The first method is the colour filtering method (CF). The second method shows the results with the TGO growth factor (TGO) implemented. The last method tested is the use of the NB classifier, instead of the SVM (NB). The calculations were performed similarly as in formulas (2) to (4).

Table 2. Test results of the analysed methods.

	TP	TN	FN	FP
CF	795	941	205	59
TGO	753	951	247	49
NB	725	799	275	201

$TPR_{CF} = 0{,}795$ $TPR_{TGO} = 0{,}753$ $TPR_{NB} = 0{,}725$
$PPV_{CF} = 0{,}931$ $PPV_{TGO} = 0{,}939$ $PPV_{NB} = 0{,}783$
$ACC_{CF} = 0{,}868$ $ACC_{TGO} = 0{,}852$ $ACC_{NB} = 0{,}762$

Fig 2. Example image from fire image database

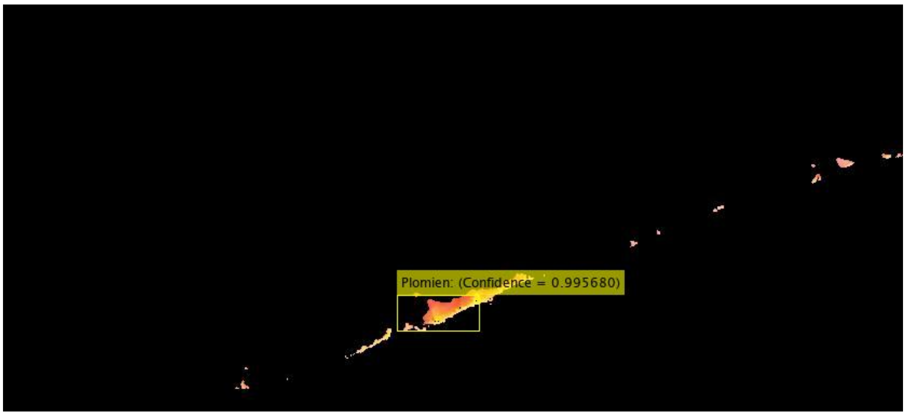

Fig 3. Figure 2 after colour filtration (True Positive).

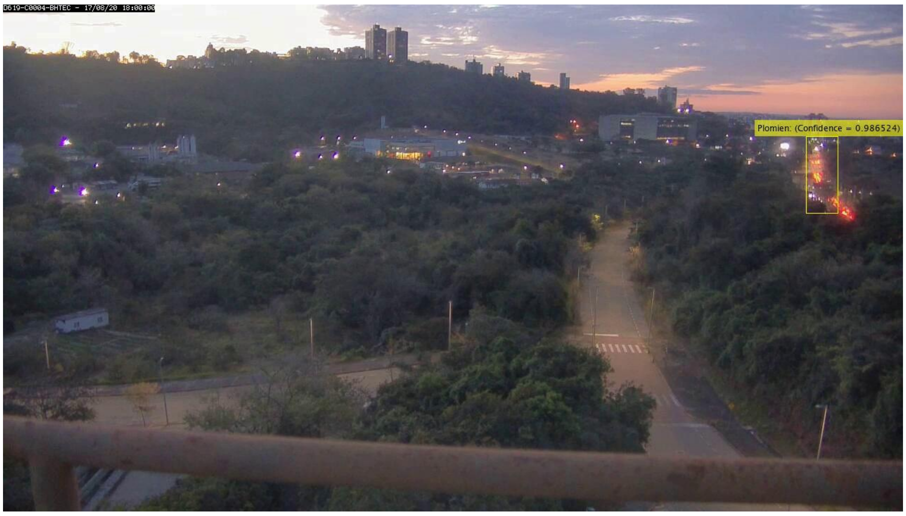

Fig 4. Example of False Positive caused by car lights.

Fig. 5 Example of False Negative.

4 Conclusions

The colour pre-filtering method proved to be the most efficient in improving the efficiency of the algorithm and achieved 86.8% efficiency, where the basic version of the algorithm achieved 77.7%, an increase of 9.1%. In addition, it is the easiest method to implement.

The method using the growth factor also improved the overall efficiency of the algorithm, but implementing additional calculations negatively affected the speed of frame analysis. The efficiency itself reached a value of 85.2%. Compared to the basic version of the algorithm, this is an increase of 7.5%

Replacing the SVM classifier with NB did not significantly affect the overall detection efficiency, which in this case dropped from 77.7% to 76.2%, so there was an overall decrease of 1.5% in terms of efficiency.

The algorithm with the NB classifier had higher sensitivity, but equally had lower precision which resulted in a higher number of false alarms (False Positive).

Figure 6 shows a graph of the effectiveness (ACC) of the different versions of the algorithm.

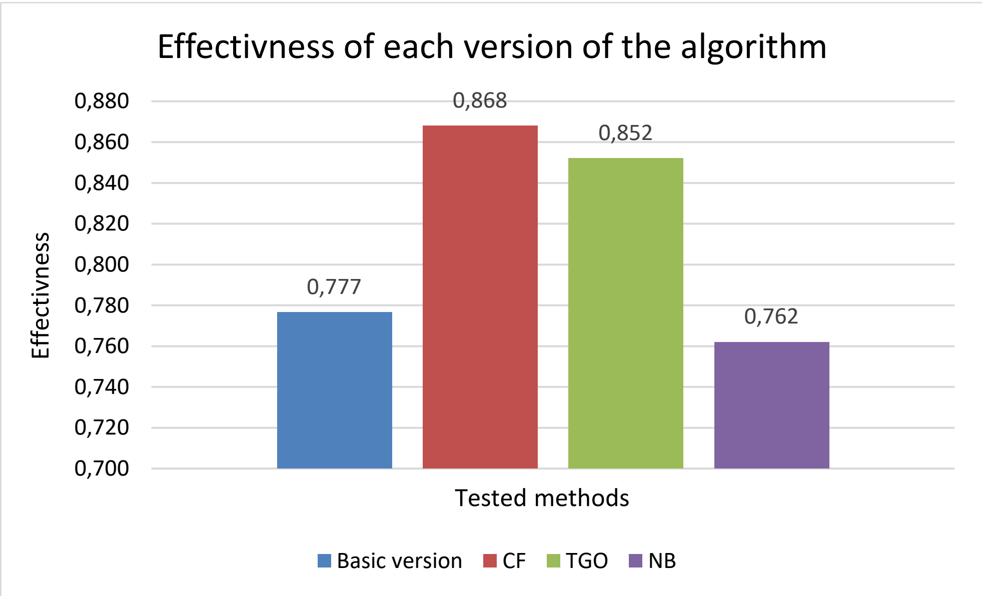

Fig. 6. Effectiveness of the algorithm with various methods of reducing the number of false alarms in VBFDs.

5 SUMMARY

VBFDS operation is based on image analysis, most often by neural networks. These systems are susceptible to any optical interference occurring in a given environment[8,9]. A disturbance can be a phenomenon that optically resembles a fire, but is not one, such as car lights. Such phenomena can directly cause a false alarm in VBFDSs[10,11], so it is necessary to implement methods that can make VBFDS even slightly immune to false alarms and thus improve its effectiveness in fire detection.

In VBFDSs it is very important to position the camera appropriately in the room in question, as with detectors in classic FASs designed to detect fire characteristics (FC)[12,13]. In addition, the camera should have the best possible technical parameters (resolution, viewing angle, focal length, etc.), as the quality of the transmitted image is crucial for correct detection. If the quality is not sufficiently high, the captured image will not be able to convey the relevant flame-related features to the algorithm. Furthermore, the correct design of the algorithm is a fundamental factor for its correct functioning, i.e. the detection of FC [14,15].

The article examines three methods for reducing false alarms in VBFDSs. Two of them proved effective in reducing the number of false alarms and raised the overall effectiveness of the algorithm. Each method was studied separately from the others. In the future, it is planned to further analyze the methods of reducing false alarms and explore the possibility of fusion of individual solutions.

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