Image Flame Recognition Algorithm Based on M-DTCWT

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Abstract. In order to improve the effectiveness of flame image feature extraction, we propose a M-DTCWT (multidirectional dual-tree complex wavelet transform) complex frequency domain feature extraction method, combined with multi-feature fusion to achieve flame recognition in multiple scenes. First, the suspected flame region is detected by the RGB-HSI mixed color space. Secondly, Combining the filter bank in the M-DTCWT with the hourglass filter bank to construct more M-DTCWT in the diagonal direction, M-DTCWT decomposition on the suspected flame region image, and extracting the improved LBP (Local Binary Patterns) texture feature and circularity feature in the low frequency coefficients. Finally, through feature fusion, the SVM (Support Vector Machine) using the cross grid search method identifies the flame. A large number of experimental results verify the effectiveness of the algorithm.

1. Introduction
Horng et al. [1] selected the HSI color space and extracted the flame region using a fixed threshold segmentation method, which can roughly segment the flame region. Jiang B [2] proposed a method of combining the global color features of the LAB histogram with the local SURF texture features to identify the flame, which has a certain improvement in the recognition rate compared to the single feature or local feature, but cannot distinguish between real flame and flame-like objects. Foggia, P [3] et al. proposed a fire flame detection method based on YCbCr [4] color, shape change feature in the spatial domain and flame motion information feature. Kuang-Pen Chou et al. [5] used pixel block-based analysis of local features, where local features include the color of the flame and the immobility of the flame, and the flame was further identified by the LBP feature. This method improves the flame recognition rate in a simple scene to some extent. Sam G Benjamin et al. [6] used the HSV-YCbCr color space and the five texture features of gray-level co-occurrence matrix (GLCM) to identify the flame and achieve a higher recognition rate, but the GLCM feature is a statistical texture feature, so this method has limitations in the classification of textures at the pixel level.

The above image-based flame detection and recognition method basically extracts the flame feature in the time domain or the spatial domain. Since the spatial frequency of the actual image is complex and contains a lot of redundant information, the flame feature is not used efficiently. To solve this problem, this paper proposes a flame recognition algorithm combining RGB-HSI and M-DTCWT complex frequency feature fusion. The flame image is transformed by the M-DTCWT complex frequency domain, which not only reduces the redundant information of the ILBP feature and the
circularity feature, but also more effectively describes the geometric features of the multidirectional edges and textures of the flame image, thereby improving the recognition accuracy of the flame.

2. Suspected flame region extraction

Color is a typical feature of flame. Commonly used color spaces are HSV, RGB, HSI, YCbCr, etc. Different color spaces have different characteristics [7]. According to the characteristics of flame color, the RGB and HSI mixed color space is used to analyze the flame. The candidate flame region obtained by RGB and HSI mixed color space is then subjected to the median filtering and the closed operation by the morphological processing method, and finally the filling operation. This series of operations can better eliminate the noise and fill in small holes. This method not only eliminates some false fire areas, but also obtains a relatively complete flame region.

![Original RGB-HSI The Median filtering Closed operation Filling](image)

Figure 1. Suspected flame region extraction process

3. Extraction of complex frequency domain features of flame region

3.1. M-DTCWT (Multidirectional dual-tree complex wavelet transform)

In order to further increase the directional selectivity of DTCWT (Dual-Tree Complex Wavelet Transform) [8], an hourglass decomposition filter [9] combined reconstruction filter bank is added on the basis of DTCWT filter bank to construct an M-DTCWT filter bank. The input image is transformed by M-DTCWT.

If the complex scaling function is equal to

\[ \Phi_{i,j}(n_1, n_2) = \Phi^{re}_{i,j}(n_1, n_2) + \sqrt{-1}\Phi^{im}_{i,j}(n_1, n_2), \]

and the complex wavelet function can be expressed as

\[ \Psi_{i,j,k}(n_1, n_2) = \Psi^{re}_{i,j,k}(n_1, n_2) + \sqrt{-1}\Psi^{im}_{i,j,k}(n_1, n_2). \]

Here, \( n_1 \) and \( n_2 \) are the corresponding pixels in the image, \( j \) and \( k \) are the scaling and translation index, \( i \) are the number of directional subbands, and \( re \) and \( im \) are the decomposed real and imaginary parts, respectively. Then the two-dimensional image decomposed by M-DTCWT can be represented by a series of complex scaling functions and complex wavelet functions.

\[ f(n_1, n_2) = \sum_{k \in \mathbb{Z}} c_{j,k} \Phi_{j,k}(n_1, n_2) + \sum_{i=1}^{8} \sum_{j,k} d^{(i)}_{i,j,k} \Psi^{(i)}_{i,j,k}(n_1, n_2) \quad (1) \]

Where \( Z \) is a natural set, \( c_{j,k} = \left\langle MS^{(b)}(n_1, n_2), \Phi_{j,k}(n_1, n_2) \right\rangle \) is the scale coefficient, and \( d^{(i)}_{i,j,k} = \left\langle MS^{(b)}(n_1, n_2), \Psi_{i,j,k}(n_1, n_2) \right\rangle \) is the complex wavelet coefficient in the \( i \) direction.

The multi-scale and multidirectional decomposition of the image of fire flame region extracted from RGB-HSI color space is carried out to obtain the decomposed high and low frequency subband coefficients, and then the subband coefficients are divided into four low frequency subblocks and eight high frequency subblocks. Average low-frequency subblock are obtained by averaging 4 low-frequency subblocks and average high-frequency subblock are obtained by averaging 12 high-frequency subblocks.
As can be seen from Fig. 2, the flame region is decomposed into low frequency blocks and high frequency blocks by M-DTCWT, the low frequency blocks represent the detail information of the flame and the high frequency blocks represent the contour information of the flame. Therefore, the low frequency block can be used to extract the ILBP feature and the circularity feature of the flame, and the high frequency block can be used to extract the edge feature\[10\] of the flame.

3.2. The improved LBP texture feature in complex frequency domain

In order to make LBP \[11\] \[12\] multidirectional selectivity, we consider using the local features of the image to assign a direction to the central pixels in each domain. On the basis of the traditional LBP algorithm \[11\], the centroid of the circular region centered on the pixel is determined by the first and the zeroth moment of the image, and the main direction of the local texture of the region is determined by the centroid. The multidirectional LBP feature, which is very helpful for the feature similarity calculation, also improves the accuracy of fire classification.

After obtaining the central pixel of a certain field, the image moments $G(x, y)$ is calculated, and the calculation method is as follows:

$$m_{p,q} = \sum_{x,y} x^p y^q G(x, y)$$ \hspace{1cm} (2)

According to the image moment theory, the first moment and the zeroth moment of the image are used to calculate the centroid $C$ of the central pixel field. The calculation formula is as follows:

$$C = \left( \frac{m_{01}}{m_{00}}, \frac{m_{10}}{m_{00}} \right)$$ \hspace{1cm} (3)

According to the imaging principle of the camera, the distribution of the pixels in the image area is not uniform, so the centroid $C$ and the geometric center $O$ of the image moment $G(x, y)$ are not in the same position. Then a vector $\overrightarrow{OC}$ can be constructed. The angle between $\overrightarrow{OC}$ and $X$ is defined as the main direction of the central pixel in a certain field. The calculation formula of the angle $\theta$ is as follows:

$$\theta = \tan^{-1} \left( \frac{m_{01}}{m_{10}} \right) = \tan^{-1} \left( \frac{\sum_{x,y} y G(x, y)}{\sum_{x,y} x G(x, y)} \right)$$ \hspace{1cm} (4)

Through the above process, combined with the method of calculating the LBP features of rotation invariant mode \[12\], we can finally get the LBP features of multiple directions. Based on M-DTCWT processing of fire flame region, the low frequency coefficient features are obtained. The size of four low frequency blocks and one average low frequency block are 320*240, and each low frequency block is divided into 8*8 cells. In this paper, we use ILBP feature extraction of gray scale invariant + rotation invariant + uniform pattern, so there are nine patterns in each cell histogram. All cells of each low frequency block are combined to form a feature vector 9*64 dimensions, and the other four low frequency blocks are fused into a feature vector group 5*9*64 dimensions to describe the ILBP feature of this flame image.
3.3. The circularity feature of the complex frequency domain

The circularity is a measure of the degree of circular similarity. According to the circumference and the area of the circle, the formula for calculating the circularity is defined:

$$C = \frac{L^2}{4\pi S} \quad (5)$$

Where $L$ is the perimeter of the flame boundary and $S$ is the area of the flame. The acquired flame image is transformed into binary image, 1 is fire flame region (white region) and 0 is non-fire flame region (black region). The perimeter can be obtained by the boundary algorithm. The vertical or horizontal distance between two adjacent flame pixels is unity 1. The distance between the other two points is obtained by using the Pythagorean theorem. The maximum circularity of the circular object is 1, and the more complex the object is, the smaller the value is.

Based on the M-DTCWT processing fire flame region to obtain the low frequency coefficient feature, the circularity feature of the five low frequency coefficient blocks is extracted by the above algorithm and merged into one feature vector group. The circularity feature and the ILBP feature set are optimally weighted [13], and then the circularity feature and the ILBP feature are serially fused into a set of $(5*9*64+5)$ dimensional feature vector groups.

4. Experimental results and analysis

The algorithm flow of this paper is as follows: input training sample image for image preprocessing, then extract the suspected flame region through the color space of RGB-HSI, then process the extracted region with M-DTCWT to obtain the low frequency image, then realize ILBP feature and circularity feature extraction on low frequency images and the fusion of ILBP feature and circularity feature, and finally the optimal SVM is obtained by the cross-grid search method. The test samples are put into the optimal SVM for flame recognition.

![Figure 3. Algorithm flow chart](image)

The experimental environment of this paper is as follows: Window7 system, Intel(R) Core(TM) i5-6200U CUP @2.30GHz, 2.40GHz, 4GB RAM. There is currently no authoritative and complete library of photo and video detection samples for fire flame detection. Part of the experimental samples comes from self-recorded video images, part of which comes from the Internet. There are 7858 images in total, and the image size is 640*480. It comes from different occasions, including night indoor and outdoor fire flame video images, night indoor and outdoor non-fire flame video images, and daytime indoor and outdoor fire flame video images, indoor and outdoor non-fire flame video images during the day.

In the experimental data set, a total of 5800 flame images and 2400 non-flame images were selected as training samples, and the remaining 2058 were used as test samples. The SVM kernel function is selected as the radial basis kernel function and the optimal parameter kernel parameter $g$ and the penalty parameter $c$ [14] are obtained. The optimal parameters of RGB-HSI+LBP+circularity algorithm(Algorithm 1)is $c=4$, $g=0.25$. The optimal parameters of the algorithm are $c=5.6569$, $g=0.25$. The parameters of SVM of this algorithm and RGB-HSI+LBP+ circularity algorithm were changed to the optimal parameters, and then the test images were tested. The following is the recognition rate of the four algorithms.
The image of indoor fire and building fire is relatively clear, and the flame features are more obvious. The difference between indoor flame and surrounding environment is large, and the interference factors are small. Therefore, the recognition rate is relatively high. Forest fire flames are greatly affected by the environment such as sunlight and wind. The flame feature may be unclear, and the noise is large, so the recognition rate will decrease. For night vehicles, the recognition rate is not very high due to the influence of street lights and some police cars. The neon lights flashing at night are similar in color to the fire flame and their circularity are similar. The probability of false detection is large, which will reduce the detection rate.

The fire flame image is processed by M-DTCWT, and the circularity and texture features are extracted in the low frequency image to detect the fire flame. It can be seen from the experimental data in Table 1 that the recognition rate of the algorithm in the five scenarios is obviously higher than that of Algorithm 1, indicating that the image flame recognition algorithm based on M-DTCWT can improve the efficiency of circularity and ILBP feature extraction, and the fire recognition rate has been improved on the basis of the original, so it has a good effect on fire flame image recognition.

| Image description         | Method                                      | Average recognition rate |
|---------------------------|---------------------------------------------|--------------------------|
| Indoor flame scene        | YCbCr-HSV+GLCM                              | Reference 6, 90.01%      |
|                           | Local Feature (YCbCr+Fire source analysis)+LBP | Reference 5, 90.66%      |
|                           | RGB-HSI+LBP+circularity                     | Algorithm 1, 90.36%      |
|                           | RGB-HSI+M-DTCWT+ILBP+circularity            | This paper, 93.97%       |
| Outdoor flame scene       | YCbCr-HSV+GLCM                              | Reference 6, 87.45%      |
|                           | Local Feature (YCbCr+Fire source analysis)+LBP | Reference 5, 89.1%      |
|                           | RGB-HSI+LBP+circularity                     | Algorithm 1, 90.34%      |
|                           | RGB-HSI+M-DTCWT+ILBP+circularity            | This paper, 93.08%       |

It can be clearly seen from Table 2 that compared with the reference [6], the reference [5] and the algorithm 1, the proposed method combining the RGB-HSI color space and the M-DTCWT complex frequency domain feature fusion method has higher and more stable recognition rate.

5. Conclusion

The suspected flame region is segmented by RGB-HSI color space, and the ILBP and circularity feature are extracted from the suspected flame region by W-DTCWT at low frequencies for flame recognition. Experiments show that the flame recognition algorithm has a high recognition rate and can adapt to many complex scenes and has good robustness. The main innovations of the experiment are: Combined with W-DTCWT, the complex frequency domain feature extraction of images can not only reduce the problem of inefficient use of features due to a large amount of redundant information, but also achieve more stable ILBP features and circularity features in the frequency domain and the high accuracy of
flame recognition. On the other hand, W-DTCWT decomposes the image in multiple directions, which increases the more effective ILBP and circularity features and improves the flame recognition rate.

References
[1] Wen-Bing Horng, Jian-Wen Peng, A New Image-Based Real-Time Flame Detection Method Using Color Analysis. Proceedings of 2005 IEEE International Conference on Networking, Sending and Control, March 2005, pp:100-105.
[2] Jiang B, Lu Yi, Towards a solid solution of real-time fire and flame detection. Multimedia Tools and Applications, 2015, 74(3):698-705.
[3] Foggia, P., Saggese, A. Vento, M. Real-time fire detection for video surveillance applications using a combination of experts based on color, shape, and motion. IEEE Trans Circuits Syst Video Technol, 2015, pp:1545–1556.
[4] Premal C E, Vinsley S, Image processing based forest fire detection using YCbCr colour model[C]. International Conference on Circuit, Power and Computing Technologies. IEEE, 2014.
[5] Kuang-Pen Chou, Mukesh Prasad, Deepak Gupta, Block-Based Feature Extraction Model for Early Fire Detection. IEEE, August 2017.
[6] Sam G Benjamin, Radhakrishnan B, Nidhin T G, Extraction of Fire Region From Forest Fire Images Using Color Rules and Texture Analysis. 2016 International Conference on Emerging Technological Trends [ICETT], 2016.
[7] WU Xiyin, YAN Yunyang, DU Jing, Fire detection based on fusion of multiple features[J]. CAAI Transactions on Intelligent Systems, 2015, pp:240-247.
[8] J.W. Selesinick, R.G. Baraniuk, N.G. Kingsbury, The dual-tree complex wavelet transform. IEEE Signal Processing Magazine, 2005, pp:123-151.
[9] Yue M.Lu, Minh N.Do, A Mapping-Based Design for Nonsubsampled Hourglass Filter Banks in Arbitrary Dimensions. IEEE Transactions on Signal Processing, 2008, pp:1466-1478.
[10] OUYANG Ji-neng, BU Le-ping, YANG Zhi-kai, WANG Teng, An Early Flame Identification Method Based on Edge Gradient Feature. IEEE, 2018, pp:642-646.
[11] Mehta R, Egiazarian K, Dominant Rotated Local Binary Patterns (DRLBP) for texture classification[J]. Pattern Recognition Letters, 2016, pp:16-22.
[12] M. Pietikainen et al, Local Binary Patterns for Still Images. Computational Imaging and Vision 40, DOI 10.1007/978-0-85729-748-8_2, 2011, pp13-47.
[13] Bo Sun, Song Shi-Ji, Cheng Wu, A new algorithm of support vector machine based on weighted feature. Proceedings of the 2009 International Conference on Machine Learning and Cybernetics, 2009, pp: 1616-1620.
[14] LUO Xiaoyan, CHEN Huiming, LU Xiaojiang, XIONG Yang, Forecast of SVM mill load based on grid search and cross validation. China measurement & Test, 2017, pp: 132-136.