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Multi-Feature Fusion Algorithm in VR Panoramic Image Detail Enhancement Processing

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ABSTRACT VR panoramic image is an image technology that covers a wide range of scenes. Its imaging range is much larger than that of traditional imaging systems, and it can fully reflect all the information of the imaging space. Although the multi-feature fusion method has been studied for a long time, the methods of multi-feature extraction, fusion and overall optimization have not been widely studied. In view of the shadow problem in VR panoramic images, this paper proposes a multi-feature fusion VR panoramic image shadow elimination algorithm, which uses HSV color features and LBP (Local Binary Pattern) / LSFP (Local Five Similarity Pattern) texture features to obtain shadow detection results and then obtains the final detection results by fusion. The experimental results prove that while ensuring a low missed detection rate, the false detection rate is greatly reduced. The comprehensive evaluation index *Avg* in this paper is improved by 3.4% compared with the shadow elimination algorithm based on a single feature. This paper proposes an image saliency detection algorithm and image detail enhancement algorithm based on multi-feature fusion. The final saliency map is obtained through linear fusion. Experiments prove that the image detail enhancement algorithm based on multi-feature fusion mentioned in this paper has achieved excellent results. In this paper, the performance of single feature fusion algorithm and multi-feature fusion algorithm are compared. The results show that the accuracy rate of multi-feature fusion algorithm based on HSV, LBP and LSFP is 93.39%, and the effect of multi-feature fusion is better than that of single feature.

INDEX TERMS VR panoramic image, image detail enhancement, multi-feature fusion, HSV color feature, LBP / LSFP texture feature, image saliency detection.

I. INTRODUCTION

Virtual Reality (VR) technology is an interactive three-dimensional dynamic visual scene that integrates multi-source information. Image detail enhancement technology can be used in the rendering and optimization of different VR panoramic images in virtual reality technology and can generate a full range of panoramic images. The VR panoramic image detail enhancement technology is used to correlate the scene spatially and realize a realistic virtual world.

In Virtual Reality (VR), content is usually generated by creating a 360-degree video panorama of a real scene. Despite the release of many capture devices, due to their high computing requirements, it is still challenging to obtain high-resolution panoramic images and display the virtual world in real time [1]. Histogram equalization technology is widely used in the field of image enhancement. This method is introduced into the gradient field to make the image details evenly distributed in each gray level [2]. In [3], the author

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proposed an image enhancement method based on quaternion guided filter. The article uses image layering to decompose the source image into a base image and a detailed image and enhances the detail image through adaptive enhancement transformation [4]. In [5], the author proposed an image smoothing algorithm based on gradient-domain weighted least squares. The proposed detail-enhancement-exposure-fusion algorithm can better preserve the details in the saturated region. In [6], [7], the author proposed a low-illumination image enhancement algorithm. The article finally got an image with enhanced details and suitable for brightness. The algorithm shows good performance in image enhancement. In [8], the method proposed by the author improves visual comfort while maintaining a 3D presence [9]. In [10], the author proposed an image resolution enhancement algorithm based on evolutionary wavelet filter coefficients. The proposed algorithm appropriately enhances the resolution of the image. In [11], the author developed a texture-enhanced multi-exposure image fusion method based on texture features. This method improves the robustness of texture details while avoiding gradient inversion artifacts that may appear in the fused image after DL enhancement. In [12], the author conducted extensive experiments on synthetic and real low-resolution noisy text images and verified the effectiveness of the proposed system visually and quantitatively. Compared with the most advanced methods, encouraging results can be achieved in visual image quality and character recognition rate [13]. In [14], the author's algorithm can process high-resolution images on smartphones within a few milliseconds, provide a 1080p resolution live viewfinder, and is comparable to the most advanced technology on most image operators.

Among the above research methods, they all take the median or mean as the segmentation threshold of the histogram. Although the brightness information of the image to can be effectively saved, we can not make the enhanced image obtain the maximum contrast, and the image may also be over enhanced and lose the original image details. Therefore, we consider whether multi-feature fusion can have better algorithm results and integrate them.

For the performance and application of the algorithm of multi-feature fusion, domestic and foreign research teams have conducted in-depth research and analysis. In [15], the author proposed a joint vibration and acoustic diagnosis method based on multi-feature fusion and improved Quantum Particle Swarm Optimization (QPSO) -Regression Vector Machine (RVM) to diagnose mechanical failures of conventional circuit breakers. In [16], the author's method showed good performance and visualization in quantitative evaluation. In [17], [18], the author proposed a low-resolution face recognition technology based on the one-dimensional hidden Markov model and finally used the Canonical Correlation Analysis (CCA) method to combine the simplified features. In [19], the author proposes a novel visual tracking multiple sparse representation frameworks, which uses the shared attributes of different features and feature-specific attribute patterns by decomposing multiple sparsenesses. In [20], [21], to establish a robust background model and improve the accuracy of foreground object detection, the author comprehensively considers the temporal correlation of pixels at the same position in the video image and the spatial correlation of adjacent pixels. In [22], the author proposed a quantitative evaluation model of Weibo user rights based on multi-feature fusion. The method proposed in this article is more effective than the famous PageRank algorithm in calculating the influence of user information dissemination. In [23]–[25], to improve positioning accuracy and tracking service quality, the author proposes an embedded tracking algorithm based on multi-feature fusion and visual object compression. Experimental results show that the tracking algorithm has higher accuracy, lower energy consumption, and lower delay. In [26], the closed-loop detection algorithm based on multi-scale deep feature fusion proposed by the author has higher accuracy and recall rate. In [27], [28], the author combined segmentation optimization and multi-feature fusion technology to propose an Object-Based Change Detection (OBCD) method in high-resolution remote sensing images. The qualitative analysis and quantitative analysis of the results proves the effectiveness of the proposed method.

Aiming at the common shadow problems in VR panoramic image, this paper proposes a shadow elimination algorithm based on multi-feature fusion, which uses HSV color feature and texture feature to get their shadow detection results, and then through the fusion of different shadow detection results to get the final detection results, and then eliminate the shadow to get the accurate moving target. This paper proposes an image saliency detection algorithm and image detail enhancement algorithm based on multi-feature fusion, which separates color features and texture features, and then obtains the final saliency map through linear fusion. In this paper, the performance of the single feature and multi-feature fusion algorithms are compared. The effect of combining LBP and LSFP input for feature learning is far better than that of the single input LBP feature or LSFP feature.

II. MULTI-FEATURE FUSION ALGORITHM IN DETAIL ENHANCEMENT OF VR PANORAMIC IMAGE

A. SHADOW REMOVAL ALGORITHM OF VR PANORAMIC IMAGE BASED ON MULTI-FEATURE FUSION

1) COLOR CHARACTERISTICS

The HSV color space is consistent with the colors perceived by human vision. Hue H represents the type of color, and the H component value is represented by the angle [0°, 360°], and red and green correspond to 0 ° and 120 °, respectively. The HSV color space can separate the chroma and lightness information, and the chroma includes hue H and saturation S. The conversion formula of RGB to HSV color space is as follows:

$$H_1 = \arccos\left\{\frac{[(R-G)+(R-B)]/2}{\sqrt{(R-G)^2+(R-B)(R-G)}}\right\},$$

$$H = \begin{Bmatrix} H_1 & if\ B \le G \\ 360 - H_1 & otherwise \end{Bmatrix}$$
$$S = \frac{\max(R, G, B) - \min(R, G, B)}{\max(R, G, B)}, \quad V = \frac{\max(R, G, B)}{255} \tag{1}$$

In the HSV color space, the shadow of the VR panoramic image area and the HSV component of the real target are significantly different. The hue and saturation of pixels in the shadow area vary within a certain range, while the lightness value decreases. The VR panoramic image area can be judged by the following formula. When a pixel meets the shadow judgment condition, the value of Sh_{HSV} is equal to 1, and the pixel is judged as a shadow.

$$Sh_{HSV}(x, y) = \begin{cases} 1 & if\ \left|I_t^H - I_b^H\right| \le T_H \\ & and\ \left(I_t^S - I_b^S\right) \le T_S \\ & andT_{sV} \le I_t^V / I_b^V \le T_{bV} \\ 0 & otherwise \end{cases} \tag{2}$$

Among them, I_t^H, I_t^S, and I_t^V respectively represent the hue value, saturation value, and lightness value of the image to be detected, and I_b^H, I_b^S, and I_b^V respectively represent the hue value, saturation value and lightness value of the background image. Sh_{HSV} is a shadow detection result based on the HSV color space, and 1 represents shadow. T_H, T_S, T_{sV}, and T_{bV} are fixed thresholds. Generally, choosing a suitable value according to the specific scene can obtain better shadow detection results.

2) LBP TEXTURE FEATURE (LOCAL BINARY PATTERN, LBP)

The improved LBP calculation process is shown in the following formula, where the size of the threshold T_{ibp} is the range that allows the gray value to fluctuate.

$$LBP(x, y) = \sum_{i=0}^{7} d\left(I_i - I\right)^* 2^i$$
$$d(x) = \begin{cases} 1 & if\ x \ge 0 \\ 0 & otherwise \end{cases}$$
$$LBP(x, y) = \sum_{i=0}^{7} d\left(I_i - I + T_{ibp}\right)^* 2^i \tag{3}$$

The working process based on LBP texture features is as follows: select pixels *(x, y)* of the VR panoramic image area, and calculate the LBP texture feature string pattern results $LBP_F(x,y)$ and $LBP_B(x,y)$ of the pixel in the current frame and background image to be detected. The degree of similarity between two LBP texture features is judged by Hamming distance. When the Hamming distance is very small, determine whether the above two LBP texture features are the same and whether the pixel belongs to the shadow area. The specific detection process is shown in the formula, where Sh_{LBP} is the shadow detection result based on the LBP texture feature, and 1 indicates that it is determined as a shadow.

3) LFSP TEXTURE FEATURES (LOCAL FIVE SIMILARITY PATTERN, LFSP)

The shadow elimination algorithm only needs to judge the similarity result of the LFSP operator of the area to be detected and the corresponding background, and does not need specific texture feature values. Therefore, only the result of the string pattern needs to be calculated. The specific calculation process is as follows. The specific calculation process is shown below.

$$\begin{aligned} &LFSP(x, y) \\ &= \{d\left(I_0 - I\right), d\left(I_1 - I\right), \ldots, d\left(I_i - I\right), \ldots, d\left(I_{23} - I\right)\} \\ &d(x) \\ &= \begin{cases} -2 & if\ x < -\alpha_b^* I \\ -1 & if\ x < -\alpha_s^* I\ and\ \ x \ge -\alpha_b^* I \\ 0 & ifx \le \alpha_s^* I\ and\ \ x \ge -\alpha_s^* I \\ 1 & ifx > \alpha_s^* I\ and\ x \le \alpha_b^* I \\ 2 & ifx > \alpha_b^* I \end{cases} \end{aligned} \tag{4}$$

where α_s and α_b are the size threshold coefficients respectively, $I_i - I$ is the result of the subtraction of the gray value of the domain pixel *i* and the center pixel, and the subtraction result is categorized into five relative thresholds to obtain the string pattern result. The size of the LFSP operator is 5 × 5, and the length of its string value is 24.

B. VR PANORAMIC IMAGE SALIENCY DETECTION ALGORITHM BASED ON MULTI-FEATURE FUSION

1) CONTRAST BASED ON COLOR FEATURES

For an image, after using superpixel segmentation, the significance value of any superpixel block r_k is realized by calculating the color distance between each other, the formula is as follows:

$$S\left(r_k\right) = \sum_{r_k \ne r_i} w\left(r_i\right) D_r\left(r_k, r_i\right) \tag{5}$$

In the formula, $D_r(r_k,r_i)$ represents the color distance between the two superpixel regions r_k and r_i; $w(r_i)$ is the number of pixels in the region r_i, representing the weight of the region r_i. The reason why the number of pixels is used as the weight is that the more pixels with similar colors in the superpixel, the larger the area occupied by the VR panoramic image, and according to experience, it is more significant. Simply speaking, it increases the influence of the closer distance region and weakens the influence of the longer distance region:

$$S\left(r_k\right) = w_s\left(r_k\right) \sum_{t_k \ne t_i} exp\left(\frac{D_s\left(r_k, r_i\right)}{-\sigma_s^2}\right) w\left(r_k\right) D_r\left(r_k, r_i\right) \tag{6}$$

In the formula, σ_s^2 is the strength of the spatial weight. The larger σ_s^2 is, the smaller the influence of the spatial weight will be. The value is 0.4 in the experiment. $D_s(r_k,r_i)$ represents the spatial distance between r_k and r_i in the superpixel region; $w_s(r_k)$ is a control item used to control the attraction of non-image boundary regions to human vision.

2) CONTRAST BASED ON TEXTURE FEATURES

The connection between the salient area in the VR panoramic image and the image boundary is much smaller than the connection between the background and the boundary. The salient region is large and compact in an image, and it is only slightly or basically not connected with the boundary of the image; while the background region is more obviously in contact with the boundary of the image. Therefore, define a variable to evaluate the degree of connection between a region R in the image and the image boundary:

$$BndCon(R) = \frac{|\{p|p \in R, p \in Bnd\}|}{\sqrt{|\{p|p \in R\}|}} \tag{7}$$

where Bnd is the set of all boundary blocks of the image, p is any image block. As shown in Figure 1, it is the geometric interpretation of the image boundary connectivity *BndCon(R)*.

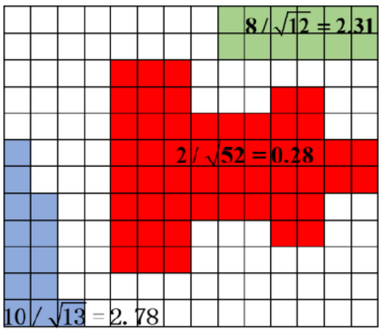


FIGURE 1. Geometric interpretation of the boundary connectivity of the image area.

In Figure 1, the red area is a significant area, which is more connected to the image boundary; the blue and green areas are more connected to the non-significant area. It can be found that the boundary connectivity of the background area of any image is in principle relatively large.

3) FUSION OF TEXTURE FEATURES AND COLOR FEATURES

Saliency maps based on color features have higher contrast, while saliency maps based on texture features can accurately locate the position of salient targets. Therefore, the texture feature saliency map and color feature saliency map of the VR panoramic image need to be fused by a linear weighting method. The linear fusion formula is as follows:

$$S = \alpha S_1 + (1 - \alpha)S_2 \tag{8}$$

In the above formula, S represents the final fusion saliency map; S_1 represents the texture feature saliency map; S_2 represents the color feature saliency map. The above formula is actually a linear weighted addition of the contrast calculated in the two feature channels, where the value of α is between [0,1].

After many experiments, it has been found that for images with simple backgrounds and simple textures, α value between [0.3, 0.4] will give better detection results. For images with complex background textures, α generally needs to be set at about 0.7. Through linear weighted fusion, combining the information extracted from the texture and color feature channels can effectively increase the saliency value of the image's saliency region, and at the same time can better suppress the influence of the image edge background on the saliency region.

C. IMAGE DETAIL ENHANCEMENT ALGORITHM BASED ON MULTI-FEATURE FUSION

1) IMAGE FEATURES

We must quantify the colors in the image before extracting features. However, for the human eye, the human eye perceives these three components differently, so this paper will perform non-uniform quantization. After quantization, the three components are combined, and the formula is as follows:

$$Z = Q_S Q_V H + Q_V S + V \tag{9}$$

Among them, Q_s and Q_v represent the quantization levels of the color components S and V, respectively. We set $Q_s = 2$, $Q_v = 2$, then the above formula can be rewritten as:

$$Z = 4H + 2S + V \tag{10}$$

Therefore, after quantization, the color histogram vector can be expressed as a 1×32 one-dimensional vector.

2) TEXTURE FEATURES

In this paper, $P(x, y)$ is a two-dimensional digital image, its size is $M \times N$, and the spatial relationship it satisfies is as follows:

$$P(x, y) = \#\{(x1, y1), (x2, y2) \in M \times N\} \tag{11}$$

Among them, x in *#{}* represents the number of elements in the set, and P is a matrix of $N_g \times N_g$. In this paper, we extracted four parameters from four directions (0°, 45°, 90°, 135°), namely contrast, correlation, energy, and uniformity, and finally generated a 1×4 vector.

3) FEATURE FUSION

During fusion, this paper assigns weights according to different features to enhance the accuracy of image details, and then dynamically adjusts the weights according to different types of images to obtain better fusion results. This article assumes HSV color features, and the weights of HSV, LBP, and LSFP are ω_1, ω_2, and ω_3, respectively. We let the weight satisfy the following condition:

$$\omega_1 + \omega_2 + \omega_3 = 1 \tag{12}$$

III. EXPERIMENT

A. VR PANORAMIC IMAGE DATA SET

1) COREL-1k DATA SET

Corel-1000 image database: The database includes 10 types of VR panoramic images, and each type contains 100 VR panoramic images. They are: "Africa, Beaches, Buildings, Racing, Sunsets, Flowers, Elephants, Marine life, Flying Machines, and Mountains." The size of each image is 192 × 128, and the image format is JPEG.

2) AT & T DATA SET

The AT & T face database mainly includes face images. The AT & T database has 40 types of face images, each with 10 images, for a total of 400 images. These 10 images are composed of the same person with different expressions and ornaments, with details such as opening eyes, closing eyes, happy, unhappy, wearing glasses, not wearing glasses, etc. These images are taken at different times and under different lighting conditions. The size of each image is 92 × 112.

3) ECSSD DATA SET

The ECSSD database contains 1000 VR panoramic images with complex structures and corresponding truth images. There are 13 images in each category of the database, and all images are collected in three different orientations, which also include four conditions of expression, posture, ornaments, and lighting.

B. WORKFLOW OF IMAGE SHADOW ELIMINATION ALGORITHM BASED ON MULTI-FEATURE FUSION

The process of image shadow elimination algorithm based on the fusion of color features and texture features is shown in Figure 2. This paper has detected candidate target areas, which may have shadows. In this paper, the shadow elimination algorithm of multi-feature fusion selects this area as the candidate target area, which can reduce the time complexity. At the same time, two shadow features of color and texture are used, and the accuracy of shadow detection is improved by complementary advantages.

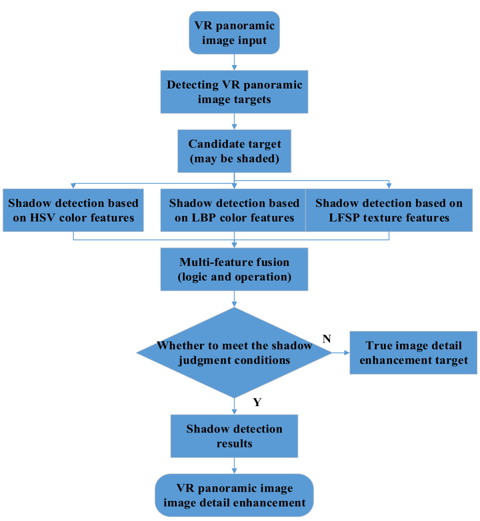


FIGURE 2. Flow chart of image shadow elimination algorithm based on multi-feature fusion.

The specific process steps of the algorithm are as follows:

Step 1: Save the shadow feature of the VR panoramic image. Calculate and store the color component and texture string pattern result of each pixel in the VR panoramic image.

Step 2: Extract the candidate target area. Extract the candidate motion target area for the current frame image to be detected. There may be a shadow in this area.

Step 3: Shadow feature extraction and match. Calculate the current HSV color component and LFSP texture string result of each pixel to be detected, combined with the background image shadow feature stored in step 1, use the formula to determine the shadow detection result of each pixel based on the LFSP texture feature and HSV color space.

Step 4: Multi-feature decision layer fusion. Perform the logical AND operation on the respective shadow detection results of the two shadow features in step three, and combine the morphological processing to obtain the final shadow detection result.

C. WORKFLOW OF IMAGE DETAIL ENHANCEMENT ALGORITHM BASED ON MULTI-FEATURE FUSION

In this paper, the color and texture features of the image are processed separately, and the image space information is fully utilized, and an image detail enhancement algorithm based on multi-feature fusion is proposed. The algorithm flowchart is shown in Figure 3.

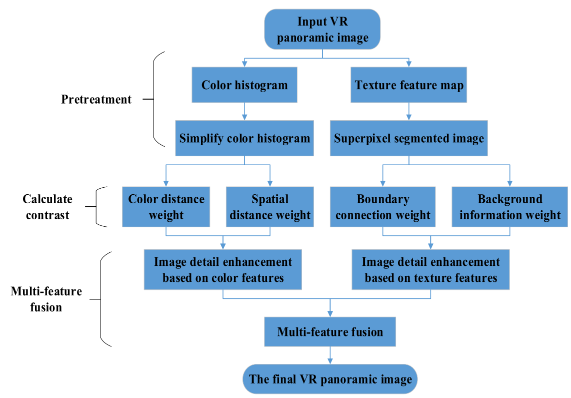


FIGURE 3. Workflow of image detail enhancement algorithm based on multi-feature fusion.

The specific process steps of the algorithm are as follows:

(1) Preprocessing: In the color feature channel, obtain the color histogram of each VR panoramic image's superpixel area, and then perform sparse histogram in the HSV color space. In the texture feature channel, the texture feature map is segmented to obtain the superpixel segmentation result of the image texture feature.

(2) Calculate the contrast: use the simplified color histogram obtained in the preprocessing stage in the color feature channel to calculate the contrast of each superpixel area on the image, and further obtain a saliency map based on the color feature. A saliency map based on the texture feature is further obtained on the superpixel segmentation map of

the texture feature obtained in the preprocessing stage in the texture feature channel.

(3) Feature fusion: Through linear weighting, the texture feature saliency map and color feature saliency map extracted from the two channels are fused to generate the final feature fusion saliency map.

D. EVALUATION METHOD OF IMAGE DETAIL ENHANCEMENT ALGORITHM BASED ON MULTI-FEATURE FUSION

This article uses three widely-used, recognized, and easy-to-understand indicators to evaluate the proposed saliency detection model. These three evaluation indicators are Mean Absolute Deviation (MAE), F value, and objective evaluation criteria.

(1) To some extent, the F value is a weighted average of the precision rate and the recall rate, reflecting the comprehensive quality of the significance test results. The calculation process is as follows:

$$F_\beta = \frac{\left(1+\beta^2\right)\cdot \ Precision \cdot Recall}{\beta^2 \cdot Precision + Recall} \tag{13}$$

(2) MAE: The average absolute error between the pixels of the saliency detection result map and the truth map is calculated:

$$MAE = \frac{1}{W \times H}\sum_{x=1}^{W}\sum_{y=1}^{H}|S(x,y) - M(x,y)| \tag{14}$$

In the formula, W and H represent the width and height of the image, $S(x, y)$ represents the true label of the pixel, and $M(x, y)$ represents the predicted label of the pixel.

(3) Objective evaluation indicators

In order to verify the objective effectiveness of the shadow elimination algorithm based on multi-feature fusion, the evaluation index is shown in the formula.

$$\eta = \frac{TP_s}{TP_s + FN_s}, \quad \xi = \frac{TP_o}{TP_o + FN_o}, \ Avg = \frac{\eta + \xi}{2} \tag{15}$$

The subscripts s and o represent shadow and target, respectively, and TP_s and TP_o represent the number of shadow pixels and target pixels that are detected accurately. FN_s and FN_o respectively represent the number of shadow pixels and target pixels that detected errors. η and ξ are the shadow detection rate and shadow resolution, respectively, and Avg is a comprehensive evaluation index.

IV. RESULTS AND DISCUSSIONS

A. ANALYSIS OF IMAGE SHADOW ELIMINATION RESULTS BASED ON MULTI-FEATURE FUSION

Figure 4 (a) is the shadow detection result obtained by the color feature in the HSV color space. From the detection result, it can be seen that the method based on the color feature almost completely detects the shadow area, but at the same time, there is a phenomenon of false detection. Figure 4 (b) and (c) are the shadow detection results obtained by using LBP and LFSP texture features in sequence. The detection results contain complete shadows, but there is a large area of false detection in the VR panoramic image area. Compared with the LBP operator, the LFSP texture reduces false detection in the VR panoramic image area. Figure 4 (d) is the final shadow detection result that combines the texture and color features. After fusion, the shadow elimination algorithm can ensure the low missing detection rate, greatly reduce the false detection rate, and achieve better shadow detection effect.

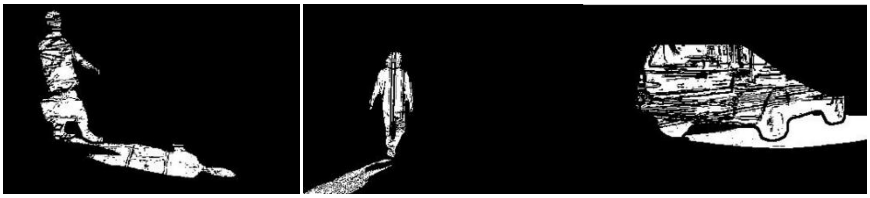
The experimental data show that there is a big gap between the comprehensive evaluation index Avg based on the shadow elimination results of LBP texture features and the improved LFSP texture features in this paper. The LFSP adopted in this paper has better texture discrimination ability. The shadow elimination algorithm based on the HSV color space has achieved a excellent detection effect under the VR panoramic image shadow detection rate η, but the shadow resolution ξ is not ideal. This is because the VR panoramic image has areas similar to the color characteristics of the shadow, such as black clothes, etc., resulting in a large area of false detection in the moving target area. In this paper, the shadow elimination algorithm of fusing color and texture features can well balance the shadow detection rate η and shadow resolution ξ by fusing shadow detection results of different features. In this paper, the comprehensive evaluation index Avg of the multi-feature fusion shadow elimination algorithm has achieved the best results compared to the above three single feature-based shadow elimination algorithms (as shown in Figure 5).

It can be seen from Figure 5 that the comprehensive evaluation index Avg of the shadow elimination algorithm based on the fusion of different features in this paper has been improved to some extent, but there are still some gaps compared with the shadow elimination algorithm based on the HSV color space. This is because most of the candidate objects in the VR panoramic image do not have clear texture features, such as solid-colored clothes and cars, which are difficult to accurately distinguish through the texture features, resulting in a lower shadow resolution ξ. In this paper, the motion shadow elimination algorithm combining color and texture features mainly improves the shadow resolution ξ and reduces false detection. The comprehensive evaluation index Avg in this paper has achieved the best results in all VR panoramic images compared to the other three single feature-based shadow elimination algorithms. The evaluation index Avg of the comprehensive detection result is improved by 3.4% relative to the shadow elimination algorithm based on the HSV color space.

B. EVALUATION AND ANALYSIS OF IMAGE DETAIL ENHANCEMENT RESULTS BASED ON MULTI-FEATURE FUSION

The average absolute error and F value of the different features on the three data sets are shown in Figure 6 and Figure 7. It can be analyzed from Figure 6 that the method based on HSV features has the highest average absolute error of the detection results on the three data sets, while the method

(a) HSV color characteristics



(b) LBP texture features

(c) LFSP texture features

(d) Multi-feature fusion

FIGURE 4. **Shadow removal results of VR panoramic images with different features and multi-feature fusion.**

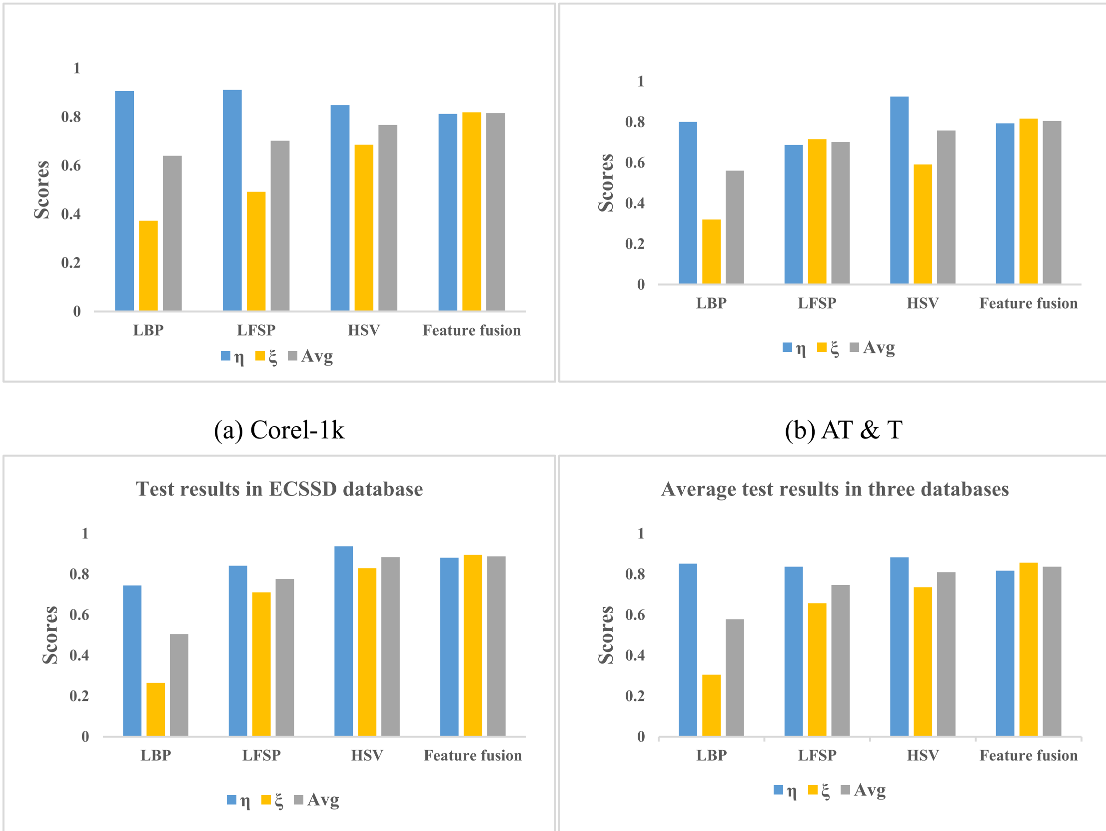
in this paper has obtained a lower average absolute error on the three data sets. Among them, the lowest average absolute error was obtained on the Corel-1k data set, which shows that the image detail enhancement algorithm based on multi-feature fusion in this paper, like several other methods, is not stable enough on different data sets.

It can be seen from the F value index chart in Figure 7 that the algorithm based on multi-feature fusion has the highest F value on the AT & T data set, and has reached the first level on the other two data sets. It was found in the experiment that F depends largely on the accuracy rate, and the impact of the recall rate is minimal. It can be seen in the figure that the histogram of the accuracy rate is often close to the height of the histogram of F, but it is quite different from the histogram of the recall rate.

On the other hand, comparing the efficiency of algorithm execution, as shown in Figure 8, it is the running speed of four algorithms on three data sets. It can be seen that the HSV feature-based method is the fastest of all methods, followed by the multi-feature fusion method in this paper. This is because the method based on the HSV feature only uses the statistical features of the color histogram of the image, and this feature is based on simple statistical calculations and does not involve a complicated calculation process, so it is the fastest to execute. However, from the previous analysis, we can see that the effect of the method based on the HSV feature is the worst, which shows that the speed is not fast enough to meet the requirements of saliency detection. The method proposed in this paper not only combines color and texture feature but also involves image superpixel segmentation, so the speed is slower than the method based on HSV features.

C. PERFORMANCE EVALUATION OF VR PANORAMIC IMAGE DETAIL ENHANCEMENT ALGORITHM BASED ON MULTI-FEATURE FUSION

To prove that the combination of texture features and color features training can enhance the details of VR panoramic



(a) Corel-1k (b) AT & T

(c) ECSSD (d) Comprehensive evaluation

FIGURE 5. Comparison of objective evaluation indexes of shadow elimination in VR panoramic images.

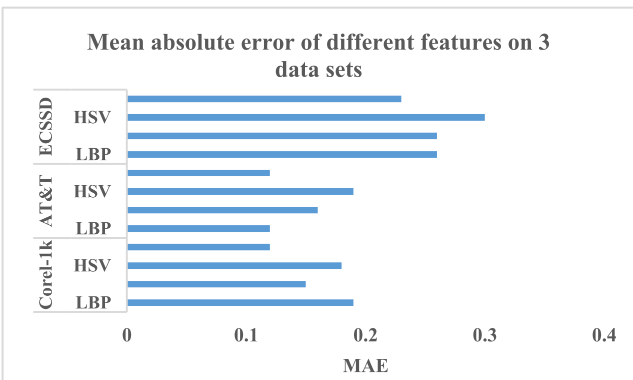


FIGURE 6. Average absolute error of different features on the three data sets.

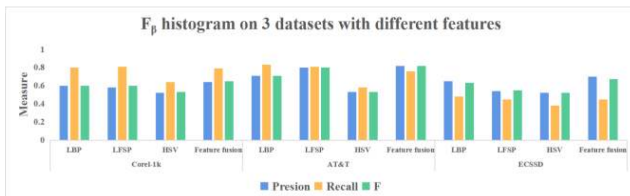


FIGURE 7. F values of different features on 3 data sets.

images, this paper conducted a comparative experiment in the data base. The test results used classification accuracy and regression correlation coefficients as evaluation indicators. In order to prove the effectiveness of this method, four comparative experiments were carried out in this paper: using HSV color features, using HSV and LBP for feature fusion, using HSV and LSFP for feature fusion, and using HSV, LBP, and LSFP for feature fusion. The test results are shown in Figure 9, and the test classification accuracy is shown in Figure 10.

It can be seen from Figure 9 that the accuracy of HSV and LBP is 90.60% and the regression correlation coefficient is 0.8491, while the accuracy of HSV is 89.71% and the regression correlation coefficient is 0.8368. The experimental effect of using LBP texture features is better than using HSV only, because the input of texture images can reduce the associative memory of redundant information and enhance the image details of VR panoramic images. LBP and LSFP obtained an accuracy rate of 92.80% and a correlation coefficient of 0.8656, which is better than the two methods of HSV and HSV & LBP. The effect of combining LBP and LSFP for feature learning is far better than that of LBP or LSFP

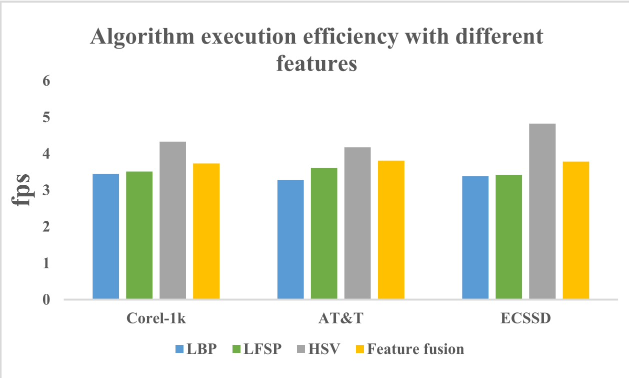


FIGURE 8. Algorithm execution efficiency of different features.

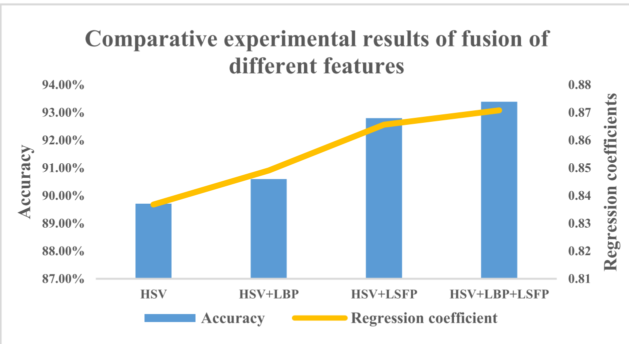


FIGURE 9. Comparison experiment results of different feature fusion.

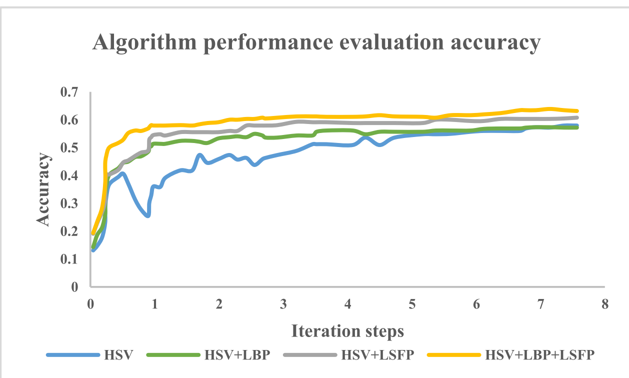


FIGURE 10. Algorithm performance evaluation accuracy.

alone. HSV, LBP, and LSFP obtained 93.39% accuracy and 0.8708 correlation coefficient. The fusion effect of HSV, LBP, and LSFP is better than that of LBP and LSFP.

It can be seen from Figure 10 that as the number of iterations increases, the accuracy rate gradually increases and finally stabilizes. After 7 iterations, the accuracy rate no longer rises, and the network tends to converge. The accuracy rate of HSV and LSFP is 92.80%, which is 2.2% higher than that of HSV and LBP, and 3.09% higher than that of HSV, while the highest accuracy rate of HSV, LBP, and LSFP is 63.39%.

V. CONCLUSION

Aiming at the shadow problems that are common in VR panoramic images, this paper proposes a multi-feature fusion VR panoramic image shadow elimination algorithm, which uses HSV color features and texture features to obtain their respective shadow detection results. Then the final detection result is obtained by fusing different shadow detection results, and then the shadow is eliminated to obtain an accurate moving target. The experimental results prove that while ensuring a low missed detection rate, the false detection rate is greatly reduced. The comprehensive evaluation index Avg in this paper is improved by 3.4% compared with the shadow elimination algorithm based on a single feature.

This paper proposes an image saliency detection algorithm and image detail enhancement algorithm based on multi-feature fusion, which separates color features and texture features. Obtain the saliency map of each feature on the two feature channels, and then obtain the final saliency map by linear fusion. Some images were randomly selected on the three data sets, comparative experiments were conducted, some effect diagrams were given, and MAE and F index diagrams were drawn. Experiments prove that the image detail enhancement algorithm based on multi-feature fusion mentioned in this paper has achieved outstanding results.

This paper compares the performance of single-feature and multi-feature fusion algorithms, and the effect of combining LBP and LSFP input for feature learning is far better than that of single input LBP or LSFP. HSV, LBP, and LSFP obtained 93.39% accuracy and 0.8708 correlation coefficient. The fusion effect of HSV, LBP, and LSFP is better than that of LBP and LSFP.

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