

Research Article

A Motion Image Pose Contour Extraction Method Based on B-Spline Wavelet

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In order to improve the accuracy of traditional motion image pose contour extraction and shorten the extraction time, a motion image pose contour extraction method based on B-spline wavelet is proposed. Moving images are acquired through the visual system, the information fusion process is used to perform statistical analysis on the images containing motion information, the location of the motion area is determined, convolutional neural network technology is used to preprocess the initial motion image pose contour, and B-spline wavelet theory is used. The preprocessed motion image pose contour is detected, combined with the heuristic search method to obtain the pose contour points, and the motion image pose contour extraction is completed. The simulation results show that the proposed method has higher accuracy and shorter extraction time in extracting motion image pose contours.

1. Introduction

Sports image pose contour extraction refers to the process of finding the required contours of sports targets in all frame images in a certain video sequence [1]. With the increasing requirements for the accuracy of image information in related fields, the maturity of the target contour extraction technology has been further enhanced. With the rapid development of science and technology today, sports image pose contour extraction technology is an important research content in the field of computer vision and artificial intelligence. This technology has an important role in many fields, such as medicine, transportation, and military [2]. At present, people's lives are inseparable from portable communication devices with camera functions. These devices produce a large amount of video information every day. These videos are processed through image pose contour extraction methods to extract valuable information and improve work efficiency in various fields. In sports images, the most basic feature is the edge. The edge is the junction of the image area and the attribute area and is the place where the image information is most concentrated. The extraction

of sports image pose contours is a prerequisite for realizing sports target detection, and it is also an important content in the field of digital image processing. Only by accurately extracting pose contour features can it be used for subsequent sports target recognition, motion trajectory tracking, sports target behavior, and so on. The work lays a theoretical foundation. Therefore, extracting the contours of sports images has more research value and challenge [3].

Literature [4] proposes a method for extracting pose contours of nonrigid human motion images. First, preprocessing of the scale-invariant feature transform (SIFT) is removed in the human motion image sequence, the human body feature extraction map is obtained, and a sequence probabilistic graph model continuity of feature sequence extraction is designed. Second, the human body appearance model is constructed. Based on the appearance model, the contour line of the current human motion frame is extracted by the high-precision contour extraction method of sequence images. The experimental results show that this method can extract continuous feature sequences, and the extracted human pose contours are more accurate and have higher efficiency and robustness. However, the extraction of

the posture contour of the human motion image in the above method takes a long time, resulting in low extraction efficiency. Literature [5] proposed a method for extracting the correct posture contour of a motion image. The correct posture area of the motion image was extracted by the adjacent frame difference method. On this basis, the snake model method was introduced, which extracts the correct posture contour of the motion image. The problem is converted to the minimization of the energy function. The level set method is analyzed, and the evolution curve is implicitly described as the zero level set of the three-dimensional continuous function surface on the motion image. When the level set function is 0, the result is contour extraction result. Through experiments comparing the effectiveness of the two proposed methods, it is found that the contour extraction effect, completeness, and information loss of the snake model method are better than other methods but inferior to the level set method. Literature [6] proposed an image-based secondary feature extraction method for abnormal gait. According to the pressure change value of the sole of the foot under different postures, a feature extraction of the abnormal gait image was completed. The feature variable data are used to construct the gait energy map of the walking contour of the target individual. At the same time, combined with the KPCA kernel method, the gait contour data after the primary feature extraction are processed for dimensionality reduction, and the secondary feature extraction of the abnormal gait is completed. The simulation results show that, under normal gait and abnormal gait, the proposed method can effectively extract the abnormal gait of the image and has a high feature extraction effect, indicating that the proposed method has strong practicability. However, the motion image pose contour extraction accuracy of the above two methods is low, resulting in unsatisfactory extraction results. The spline curve is commonly used for describing the contour of the target object in the field of image-based visual servo (IBVS). However, this method has the disadvantage of low sensitivity and poor precision when facing the camera's rotational motions. To solve this problem, literature [7] presented a visual servo system with rotational pose compensation. Literature [8] presented a multipose human detection system based on unmanned aerial vehicle (UAV) imageries in real-time. A satisfying detection accuracy of multipose human detection in complex outdoor environments can be achieved with no accelerating hardware like graphics processing unit.

Aiming at the problems of the above methods, this paper proposes a B-spline wavelet-based sports image pose contour extraction method, and the effectiveness and practicability of this method are verified through simulation experiments, which solve the problems of traditional methods and lay a foundation for sports career base.

2. Sports Image Acquisition

Aiming at the problem of the poor accuracy of image pose contour extraction in the original image pose contour extraction method, this design is carried out. In order to ensure

the accuracy of the extraction results, firstly the acquisition of sports images is completed. Setting the posture of the sports image as the directional feature of the image can well reflect the edge state of the image. The direction vector is one of the important characteristics of the image [9].

In the process of acquiring sports images, the visual system is used to perceive the direction information in the sports images. In the process of acquiring sports image poses, four sets of Gabor filters with different directions of light are used to extract the direction information in the pictures. The filter function is set in the filter as a Gaussian function modulated by a sine function, which has a certain direction selectivity and spatial connectivity [10]. The filter function can be embodied by the following formula:

$$\begin{aligned}\bar{x} &= x \cos \alpha + y \sin \alpha, \\ \bar{y} &= -x \sin \alpha + y \cos \alpha.\end{aligned}\quad (1)$$

In the above formula, \bar{x} and \bar{y} , respectively, represent the weighted average of sports image coordinate points x and y and α represents the direction of the filter. In the extraction of sports image pose contours, n is set to 4; that is, there are 4 directions in the image, and the values are, respectively, 0° , 60° , 120° , and 180° . Based on the characteristics of the filter, the extracted direction vector is the direction information perpendicular to the current filter direction in the image [11]. The direction vector of the sports image is set as the center-peripheral operator, and then the Gaussian pyramid is used to perform multiangle transformation on the image's posture direction vector feature. The multiscale angle feature difference information $\delta(A, B, \alpha)$ can be expressed as follows:

$$\delta(A, B, \alpha) = |\bar{x}(A \cdot B \cdot \alpha) - \bar{y}(B \cdot \alpha)|. \quad (2)$$

In the above formula, A and B , respectively, represent the characteristic difference value, and its value is the same [12]. Through the above formula, sports images can be obtained and used as the data basis for contour extraction.

3. Analysis and Preprocessing of Initial Sports Image Pose Contour

3.1. Analysis of Initial Sports Image Pose Contour. If you want to achieve the extraction of sports image posture contours, first the initial sports image posture contours are analyzed based on the sports image acquisition, the position of the sports area is determined, and the initial sports image posture contours are preprocessed [13]. Under normal circumstances, the location of the region segmented by the sports detection process contains the position information of the target in the previous frame and also contains the shape of the current frame, and the result of the sports segmentation indicates the current image position of the target. Therefore, the image difference method based on the statistical model is used to complete the sports segmentation. In the process of assuming that the target is moving, the camera equipment is still, the image noises of the two frames before and after are not correlated, and the mixed noise of the lens and the environment obeys the Gaussian

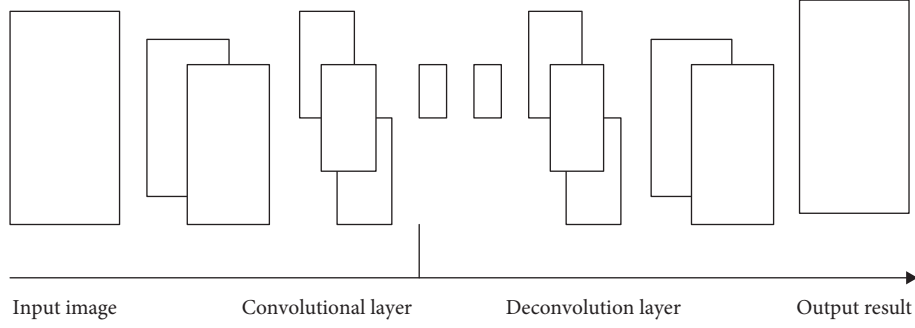


FIGURE 1: Model building process.

distribution of $\sigma^2/2$, and $D(k)$ is assumed to be the difference image of the two frames before and after. Among them, k represents a random pixel in the image. If $D(k)$ is accumulated in the field $w(k)$, σ is used for normalization processing. The specific structure is as follows:

$$\Delta^2(k) = \sum_{i \in w(k)} \left(\frac{D(k)}{\sigma} \right)^2. \quad (3)$$

Assuming that none of the pixels in $w(k)$ are moving, then the normalized difference $D(k)/\sigma$ of all pixels in this window will all obey the $N(0, 1)$ distribution, then the difference sub and Δ^2 needs to obey the χ_m^2 distribution, and the degree of freedom m represents w number of pixels in the middle. In this way, the probability distribution $p(\Delta^2|H_0)$ can be obtained, in which H_0 represents that the pixel position has no movement [14].

An appropriate small confidence level $10^{-6} \leq \alpha < 10^{-2}$ is chosen, and the corresponding threshold l_a according to the χ^2 distribution table is obtained, so that $\alpha = p(\Delta^2 > l_a | H_0)$ can be considered that $\Delta^2 > l_a$ pixels are relative motion [15].

Through the above statistical process, the position of the sports area of the sports image is obtained, and the initial sports image posture contour analysis is completed. Morphological processing is performed on it, noise is removed, and this is used as the contour data of the initial sports image.

3.2. Convolutional Neural Processing. Through the above settings, the initial sports image posture contour is analyzed, and the convolutional neural network technology is used to complete the preprocessing of the initial sports image posture contour. The pixel processing of the acquired sports image is expanded, the image feature size is reduced and restored layer by layer, and the deconvolution layer is used to obtain the human contour feature map of the image [16]. The operation process is displayed as shown in Figure 1.

The convolutional layer and the pooling layer are combined to extract the posture features of the sports image. The fully connected layer and the Softmax layer complete the extraction of global features and the classification output. In order to ensure the effectiveness of the image model acquisition, the largest pooling form in the VGG16 grid pooling is selected, as shown in Figure 2. The pooling window is set to the size of 4×4 , and the moving step is set to 4.

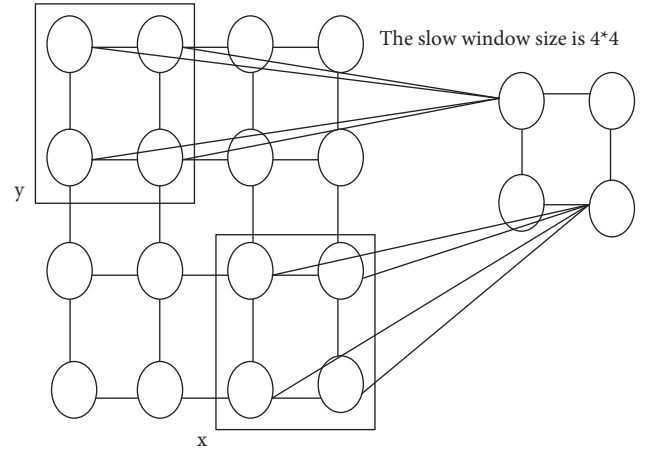


FIGURE 2: Schematic diagram of maximum pooling.

The sports image processed by the maximum pooling network is transformed into a one-dimensional feature vector after multiple connection layers, and the Softmax layer is used to complete the category processing, and then the posture in the sports image is obtained. The image information obtained by using the convolution network is not accurate enough. In this design, a deconvolution process is added, and the process is realized by bilinear interpolation by merging the multistage output results of the neural network. The corresponding feature points of the image contour acquired for the first time are set, and its pixel value is obtained, and the interpolation method is used to obtain the pixel value of the middle point of the image. The above pixel values are used to fill the pooled graphics to the original image size [17].

Through the above settings, the magnified image quality is improved, and the problem of missing pixel values due to convolutional neural processing is avoided. This setting has its own filter attribute, which can reduce the occurrence of unclear image posture contours and improve the detection accuracy of post-processing motion image pose contours.

4. Pose Contour Detection of Sports Images Based on B-Spline Wavelet

Through the preprocessed initial sports image posture contour obtained above, B-spline wavelet theory is used to detect it. The wavelet transform of the known signal $f(X)$ at any scale S and direction X is defined as follows:

$$W_S f(X) = f * \psi_S(x) = \int f(t) \psi_S(x-t) dt. \quad (4)$$

In the formula, $\psi_S(x)$ is the expansion of the mother wavelet $\psi(x)$ on the scale factor S , which is called the wavelet function. The wavelet function $\psi(x)$ is used as the first and second derivatives of the smoothing function $\theta(x)$:

$$\psi(x) = \frac{d\theta(x)}{dx}. \quad (5)$$

When using the maximum point edge detection method (canny), the wavelet transform multiscale edge detection is actually convolution smoothing the image surface with a smooth function $\theta(x)$ expansion, and then the canny edge detection method is used. Generally speaking, the extreme point detection is more advantageous than the zero-crossing detection because the zero-crossing detection is more susceptible to noise interference, and sometimes the zero-crossing response is not the sudden change point but the turning point of the signal in the slow-changing interval.

Taking $\beta_{2^{-1}}^{n+1}(x)$ as the smoothing function $\theta(x)$, corresponding to the local extremum detection, the Fourier transform is as follows:

$$\psi^n(w) = iw \left(\sin c \frac{w}{4} \right)^{n+2}. \quad (6)$$

According to the derivative properties of convolution,

$$\frac{d}{dx} \beta^{n+1}(x) = \beta^n * \frac{d}{dx} \beta^0(x). \quad (7)$$

The cubic spline is used as the smoothing function $\theta(x)$ to obtain a discrete algorithm for efficient multiscale edge detection. Using cubic spline function as smoothing function and its first derivative as wavelet function, then cubic spline $\beta^3(x)$ is as follows:

$$\beta^3(x) = \begin{cases} \frac{(x+2)^3}{6}, & x \in [-2, -1], \\ \frac{-x^3}{2} - x^2 + \frac{2}{3}, & x \in [-1, 0], \\ \frac{-x^3}{2} - x^2 + \frac{2}{3}, & x \in [0, 1], \\ \frac{(2-x)^3}{6}, & x \in [1, 2]. \end{cases} \quad (8)$$

According to the determination of the cubic spline coefficients, the sports image is adjusted through a smoothing filter to adjust the parameters, through the convolution with the appropriate horizontal and vertical templates to complete the estimation of the sampling value in the image gradient direction, and then the gradient for the modulus maximum in the direction is determined, and all local nonmaximum points in the gradient direction are set to zero to realize the detection of the sports image pose contour. The expression is as follows:

$$U(x, y) = \sum f(i, j) \beta_k(x-i) \beta_l(y-j). \quad (9)$$

5. Sports Image Pose Contour Extraction

According to the detection result of the abovementioned sports image posture contour, the image posture contour is extracted. According to the highest gradient contour point obtained in the search process, it is the contour line of the first frame of the sports image pose, and other contour lines are obtained by the heuristic search method. The specific process is as follows:

- (1) Calculate the normal line of the contour point: The contour line of the sports action is set as shown in Figure 3.

Assuming that the target contour point is $p(x, y)$, the specific relation formula of the normal line of the contour point is as follows:

$$\begin{cases} x = S \cos \theta + x_0, \\ y = S \cos \theta + y_0. \end{cases} \quad (10)$$

Setting θ to represent the inclination angle of the straight line and the length from the point to $p(x, y)$ is S , then the normal vector of the contour point is shown in Figure 4.

It can be seen from Figure 4 that the normal vector 1 of straight line AB and the normal vector 2 of BC are first obtained. According to the addition and subtraction of vectors, the sum of vectors 1 and 2 can be obtained, which is the normal vector of B.

- (2) Gradient threshold: The normals of points A, B, and C are calculated. Through the method shown in Figure 5, first look for 15 points along the upper and lower parts of each line and calculate the gradient value. Then, the gradient statistical histogram is used to calculate the gradient value.
- (3) Determine the outline point of the current frame: First, Fourier transform on the first image is performed, and the Gaussian low-pass filtering method is used to reduce noise on the previous image. In the first image, a certain point is searched in the outer normal to calculate the gradient threshold. A search is performed on the points in the normal direction, the first point is stored higher than the gradient value, and it is treated as a new contour point in the immediate frame, so that the posture contour of the sports image can be obtained.

6. Simulation Experiment Analysis

In the process of this research, the design work of sports image pose contour extraction method based on B-spline wavelet was completed. In order to ensure the effectiveness of the method design in this paper, the Matlab simulation tool was used to operate in VS2010+OpenCV2.4.13, Windows10 System Intel(R) Xeon(R) CPU E5-2603v4@2.20 GHz, memory is 32 GB, and resolution is

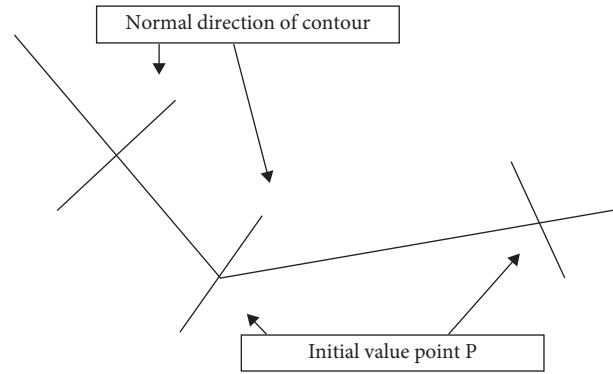


FIGURE 3: Contour of the target part.

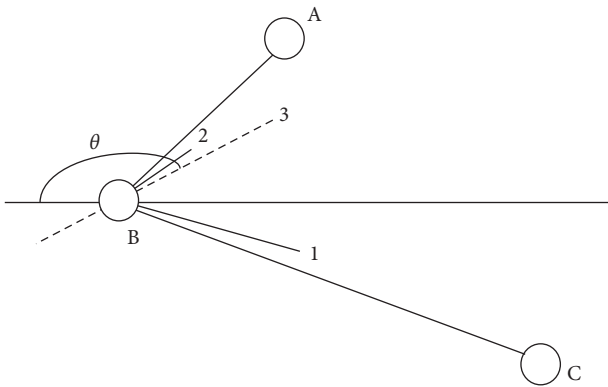


FIGURE 4: Normal vector of contour points.

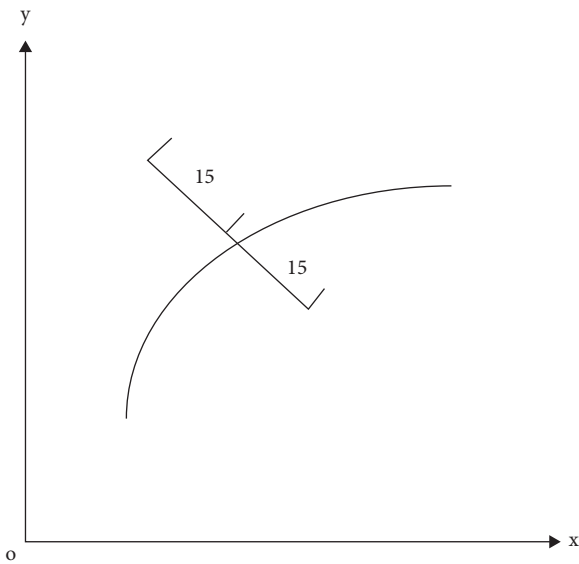


FIGURE 5: Search 15 points up and down in the direction of the normal.

800 * 600 in an environment, using comparative experiments to complete the comparison between the method in this article and the traditional method, so as to obtain the method difference.

In this experiment, a simulation experiment was used to complete the experiment. The data used in the experiment came from the Baidu gallery, and some sports pictures totaling 10,000. Unqualified images are eliminated, 1,000 images are selected as the training set for this experiment, and the image format is set in the database to 400 * 400. The 1000 images are randomly divided into 5 groups of test data, and the specific settings are shown in Table 1.

The above sample settings are used as the data basis for this experiment, and aerobics action images are selected from the Baidu gallery as the experimental samples. The original images are shown in Figure 6.

The original aerobics action image in Figure 6 is denoised, and the output result is shown in Figure 7.

Using the B-spline wavelet-based sports image pose contour extraction method proposed in this paper, the nonrigid human motion image pose contour extraction method proposed in literature [4], and the correct pose contour extraction method of sports motion image proposed in literature [5], the posture contour extraction is performed on the image samples, respectively, to verify the accuracy of the sports image posture contour extraction of the three methods. The comparison results are shown in Table 2.

According to the comparison results in Table 2, it can be seen that the sports image pose contour extraction method based on the B-spline wavelet proposed in this paper has a maximum accuracy of 98.9%, rather than rigid body movement [4]. The sports image pose contour extraction accuracy of the motion image pose contour extraction method is only 89.3%, and the sports image pose contour extraction accuracy of the motion image correct pose contour extraction method proposed in [5] is only 74.6%. The proposed method is a motion image pose contour extraction method based on B-spline wavelet, which is better than the non-rigid human motion image pose contour extraction method proposed in [4] and the motion motion image proposed in [4]. The contour extraction method is more accurate.

In order to further verify the effectiveness of the method in this paper, the B-spline wavelet-based sports image pose contour extraction method proposed in this paper, the

TABLE 1: Experimental data sample settings.

Experiment sample number	Number of samples	Sample format
S1	250	.jpg
S2	150	.jpg
S3	200	.jpg
S4	270	.jpg
S5	130	.jpg



FIGURE 6: Original image.



FIGURE 7: Denoising output image of aerobics action image.

TABLE 2: Comparison results of the three methods of sports image pose contour extraction accuracy.

Number of experiments	Literature [4] method (%)	Literature [5] method (%)	Literature [7] method (%)	Literature [8] method (%)	Method of this article (%)
10	82.3	71.7	61.6	84.8	93.6
20	82.1	70	60	80	92.4
30	84.5	70.4	60.4	80.4	92.8
40	84.9	71.9	61.1	84.9	92.6
50	85.9	70.1	60.1	80.4	92.5
60	88.4	72.5	64.3	82.5	94.1
70	81.1	73.2	63.4	83.2	93.5
80	81.8	74.6	64.7	84.5	95.8
90	89.3	72.6	64.2	82.9	96.4
100	88	73.4	63.4	83.4	98.9

nonrigid human motion image pose contour extraction method proposed in document [4], and the method proposed in document [5], the correct posture contour extraction method of the sports action image compares the extraction time of the posture contour of the sports image. The comparison result is shown in Figure 8.

According to Figure 8, this paper proposes a motion image pose contour extraction method based on B-spline wavelet, the sports image pose contour extraction time is within 30 s, the document [4] proposed the nonrigid human motion image pose contour extraction method, and Reference [5] proposed the correct posture contour extraction

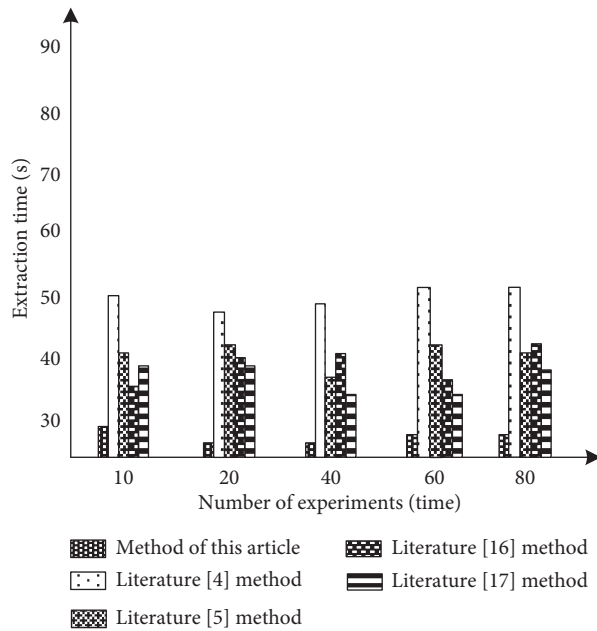


FIGURE 8: Comparison results of sports image posture contour extraction time.

method of the sports image. The extraction time of the sports image pose contour is within 55 s and 40 s. The sports image pose based on the B-spline wavelet-based sports image pose contour extraction method is proposed in this paper. The contour extraction time is shorter than that of the literature method.

7. Conclusion

In the conventional sports image detection process, the target contour feature extraction is a very complicated process, and it is necessary to study a method that is convenient for calculation. For this reason, this paper proposes a B-spline wavelet-based sports image pose contour extraction method, through B-spline wavelet theory detects the posture contours of sports images, calculates the normals of the contour points, obtains the posture contours of the sports images, and completes the image posture contour extraction. The simulation results show that the proposed method of sports image pose contour extraction effect is better, and the extraction efficiency is higher. However, with the rapid development of deep learning today, there may still be some gap between our method and deep learning method in performance. Therefore, in the future work, we need to try to integrate deep learning methods for modeling.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] X. Yu, Y. Chu, F. Jiang, Y. Guo, and D. Gong, "SVMs classification based two-side cross domain collaborative filtering by inferring intrinsic user and item features," *Knowledge-Based Systems*, vol. 141, pp. 80–91, 2018.
- [2] C. W. Peng and Z. Yang, "Image feature extraction and object recognition based on vision neural mechanism," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 34, no. 06, pp. 3340–3342, 2020.
- [3] S. Yamakawa and K. Shimada, "Feature edge extraction via angle-based edge-collapsing and recovery," *Journal of Computing & Information Science in Engineering*, vol. 18, no. 2, pp. 021001.1–021001.18, 2018.
- [4] X. Leng and H. Jiang, "An algorithm for extracting pose contours from non-rigid human motion images," *Journal of Jilin University: Science Edition*, vol. 56, no. 06, pp. 1453–1460, 2018.
- [5] W. Fatau, L. Ding, H. Yu, and Y. Zhao, "Big data analytics on enterprise credit risk evaluation of e-Business platform," *Information Systems and e-Business Management*, vol. 18, pp. 311–350, 2020.
- [6] X. Jiang and H. Zhan, "Simulation of secondary feature extraction algorithm for abnormal gait based on image," *Computer Simulation*, vol. 037, no. 003, pp. 381–384, 2020.
- [7] Y. Zhang, N. Wang, H. Wang, X. Lu, Z. Zhang, and C. Sheng, "Curve control points-based feature extraction for visual servo with rotational pose compensation," *Proceedings of the 2020 Chinese Control And Decision Conference (CCDC)*, IEEE, pp. 450–454, August 2020.
- [8] Q. Wu and Y. Zhou, "Multi-pose moving human detection based on unmanned aerial vehicle in real-time," in *Proceedings of the 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 608–613, IEEE, Xian, China, June 2019.
- [9] Q. Nie, Y. B. Zou, and C. W. Lin, "Feature extraction for medical CT images of sports tear injury," *Mobile Networks and Applications*, no. 3, pp. 1–11, 2020.
- [10] X. Ni, H. Liu, Z. Ma, C. Wang, and J. Liu, "Detection for rail surface defects via partitioned edge feature," *IEEE Transactions on Intelligent Transportation Systems*, vol. 5, no. 99, pp. 1–17, 2021.
- [11] M. Koeshardianto, E. M. Yuniarno, and M. Hariadi, "Automatic matting using edge feature-based scribbles," *IAENG International Journal of Computer Science*, vol. 46, no. 3, pp. 459–466, 2019.
- [12] V. B. S. Prasath, R. Pelapur, G. Seetharaman, and K. Palaniappan, "Multiscale structure tensor for improved feature extraction and image regularization," *IEEE Transactions on Image Processing*, vol. 28, no. 12, pp. 6198–6210, 2019.
- [13] Q. Guo, M. He, and L. An, "High-resolution remote-sensing image registration based on angle matching of edge point features," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 6, pp. 1–15, 2018.
- [14] F. Yousefiyan, H. Ebadi, and A. Sedaghat, "Shadow extraction of building using fusion of edge and point feature orientation from high resolution satellite imagery," *Journal of Geospatial Information Technology*, vol. 6, no. 3, pp. 123–145, 2018.
- [15] J. Tang, Y. Wang, Y. Wang, C. Huang, H. Liu, and N. Al-Nabhan, "Image edge detection based on singular value feature vector and gradient operator," *Mathematical Biosciences and Engineering*, vol. 17, no. 4, pp. 3721–3735, 2020.
- [16] F. Hang, G. Sun, J. Zabalza, A. Zhang, J. Ren, and X. Jia, "A novel spectral-spatial singular spectrum analysis technique for

- near real-time in-situ feature extraction in hyperspectral imaging,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 13, no. 99, p. 1, 2020.
- [17] J. Zhang, D. Li, Q. Hua, X. Qi, Z. Wen, and S. H. Myint, “3D remote healthcare for noisy CT images in the internet of things using edge computing,” *IEEE Access*, vol. 9, pp. 15170–15180, 2021.