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Retraction

Retracted: Deep Learning Algorithm in Biomedical Engineering in Intelligent Automatic Processing and Analysis of Sports Images

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] J. Bao, C. Bei, X. Zheng, and J. Wang, "Deep Learning Algorithm in Biomedical Engineering in Intelligent Automatic Processing and Analysis of Sports Images," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 3196491, 10 pages, 2022.

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Research Article

Deep Learning Algorithm in Biomedical Engineering in Intelligent Automatic Processing and Analysis of Sports Images

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In order to improve the detection and identification ability of sports injury ultrasound medicine, a segmentation method of sports injury ultrasound medical image based on local features is proposed, and the research on the sports injury ultrasound medical detection and identification ability is carried out. Methods of the sports injury ultrasound medical image segmentation model are established; the sports injury ultrasound medical image information is enhanced by using the sports skeletal muscle block matching technology; the image features are extracted; and the characteristics of sports injury ultrasound medical images are analyzed by CT bright spot feature transmission. In detail, combined with the deep convolutional neural network training method, the extracted sports injury points are automatically detected for sports injury ultrasound medical images, and the sports injury ultrasound medical image segmentation is realized. The simulation results show that this method has high accuracy for sports injury ultrasound medical image segmentation, the error value can be controlled below 0.103, and finally, the effect of zero error is achieved. It is confirmed that the method proposed in this paper has high resolution and accuracy for sports injury point detection and has strong practical application ability.

1. Introduction

In sports, there are many invisible, untouchable, dangerous events or actions, which can only be observed and analyzed from a three-dimensional perspective using traditional multimedia technology. Human stereoscopic movement information is the action information of the three-dimensional coordinates of each joint, which is the key and basis for analyzing the three competitive sports of people [1]. Image can through intelligent image processing free up and reduce time required for them [2]. Intelligent image processing refers to a kind of computer-based image processing and analysis technology that is adaptive to various applications. It is an independent theoretical and technical field, but it is also a very important technical support in machine vision. Its calculation is relatively very high [3]. The common functions of intelligent image processing technology are as follows: (1) image acquisition, (2) image preprocessing, (3) image segmentation, (4) target recognition and classification, (5) target positioning and measurement, and (6) target detection and tracking.

In addition, intelligent image processing needs to get the target object [4]. It is launched in many added functions of search of image content, which can segment the background and foreground of the image into different objects, and the intelligent image processing efficiency has been improved, but it cannot quickly eliminate noise during the intelligent image processing. They are the earliest proposed of moving image segmentation. Some practical verifications fail to be accurate, and the video objects is unclear [5].

So, based on fuzzy algorithm, this study studies images with great changes in the motion and posture of the target object, which will help for us to realize sports images [6].

The medical image processing technology has a very great development on scholars; it is used to analyze sports injury images, with the ability of sports injury and diagnosis and the ability to locate and identify injury points. It has attracted great attention of scholars. The objects of medical image processing are medical images with different imaging mechanisms. The types of medical images widely used in clinic mainly include the following: X-ray imaging (X-CT), computed tomography (CT), positron emission computed tomography (PET-CT), nuclear magnetic resonance imaging (MRI), and nuclear medical imaging (NMI), ultrasonic imaging (UI), pathological images taken under the microscope. The segmentation of sports injury ultrasound medical images is to establish a sports injury ultrasound medical image segmentation model for the feature location of the image, use the fuzzy feature analysis method to detect sports injury ultrasound medical images and information fusion identification, and improve sports injuries. The optimized detection and recognition ability of ultrasound medical images and the related sports injury ultrasound medical image segmentation methods are of great significance in sports injury analysis [7]. For domestic scholars whose detection object is obtained by using ultrasonic waves, extraction of characteristic parameters is completed according to the image and the extraction results of characteristic the method to complete the damage identification. Sanja-Gopal, a foreign scholar, proposed a finite mixture model of spatial variables and successfully applied it to MR image segmentation. The MR image imaging system was used to obtain medical images to provide help for medical personnel to analyze damaged tissue [8]. However, traditional methods generally have the disadvantages of noise and low contrast. Therefore, we propose a method of sports injury ultrasound medical images based on local features. The CT feature of a sports injury ultrasound is to perform the sports injury ultrasound medical image feature detail, and the deep convolutional sports injury ultrasound medical image is for the extracted sports injury points to achieve sports injury [9]. Therefore, an ultrasound medical video segmentation method based on local features is put forward. The overall algorithm framework is shown in Figure 1.

2. State of the Art

Machine video technology is an important branch of intelligent manufacturing. Machine video mainly uses computer to simulate human visual function, extract information from the image of objective things, process and understand it, and finally use it for actual detection, measurement, and control. Machine video technology is characterized by fast speed, large amount of information, and multiple functions. The wide application of machine vision technology in industrial automation has promoted the research process of the entire discipline and has gradually developed into a multidisciplinary science and technology such as image processing technology, computer vision technology, pattern recognition technology, artificial intelligence, and artificial nerves. A deep learning method is added on the basis of machine vision, which not only improves the efficiency of workpiece detection but also solves the detection problem of small batches and various types of workpieces in industrial production, thereby accelerating the process of intelligent workpiece detection [10]. Pattern recognition technology can be accomplished through deep learning algorithms. The deep model contains artificial neural networks with the multilayer nonlinear structure that enables it to have powerful feature expression capabilities and the ability to model complex tasks. The parallelization framework and test acceleration method for deep models are an important cornerstone for deep learning to become practical. There are many open-source implementations for different deep models, and companies such as Google, Facebook, Baidu, and Tencent have also implemented their own parallelization frameworks [11]. Deep learning has brought artificial intelligence to a new level and will have a profound impact on a large number of products and services. Deep learning is a kind of machine learning, and machine learning is the only way to achieve artificial intelligence. Deep learning has made many achievements in search technology, data mining, machine learning, machine translation, natural language processing, multimedia learning, voice, recommendation and personalization technology, and other related fields. Deep learning makes machines imitate human activities such as audio-visual and thinking, solves many complex pattern recognition problems, and makes great progress in artificial intelligence-related technologies. In 2006, Geoffrey Hinton, a professor of computer science at the school, proposed an unsupervised layer-by-layer testing (DBN), which brought hope for testing deep neural networks. In 2012, Hinton significantly reduced the Top 5 error rate from 26% to 15% for classification problems on ImageNet, the largest image database at present. In 2013, deep learning expert Yann LeCun used deep learning to explore the massive information contained in user pictures and other information, hoping to provide users with a more intelligent product experience in the future [12].

As a dynamic discipline, machine vision detection technology has broad application prospects in modern manufacturing with the addition of deep learning algorithms. Baniukiewicz P proposes a complex classifier composed of artificial neural network and fuzzy logic system to detect welding quality, thereby ensuring the safe development of products and structures. This classifier has better performance and flexibility than common neural network classifiers; Yundong Li et al. proposed Fisher's Autoencoder (FCSDA) to efficiently detect classes. This scheme is more effective in defect detection of periodic pattern warp knitted fabrics; Adriana Birlutiu et al. propose an automated defect management system based on machine learning and computer vision, which analyzes images of products through convolutional neural networks and predicts whether the product is defective. The algorithm can detect and quantify different types of defects in porcelain products [13].

3. Methodology

3.1. Introduction to Integrated Learning. Using ultrasonic image segmentation can obtain the parameters of human organs, which is of great significance to evaluate the function of human organs. However, ultrasonic images have many problems, such as large speckle noise, fuzzy region, weak boundary, and difficult to locate the region of interest (ROI), which leads to the current automatic segmentation technology that cannot guarantee the segmentation accuracy but only relies on manual segmentation of the target region, which has a huge workload and strong subjective factors. In order to improve the recognition degree of sports injury

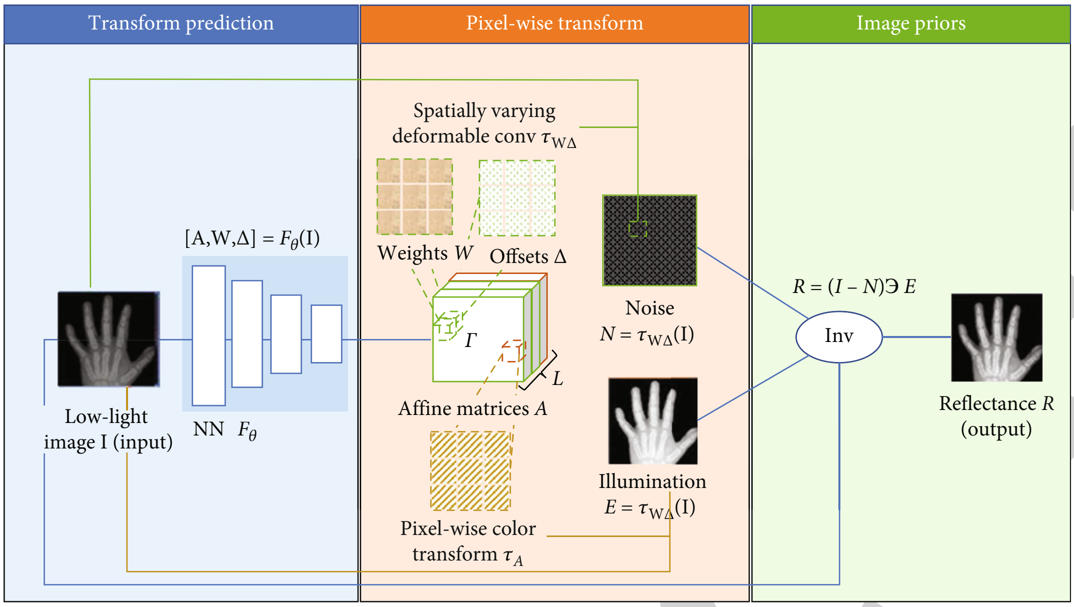

Figure 1: Sports injury ultrasound medical image segmentation framework based on local features.

ultrasound medical image segmentation, a feature extraction and information sampling model of sports injury ultrasound medical image was established, combined with high-resolution CT scanning method; the image information of sports injury ultrasound medicine was collected. The ultrasonic medical image detection of sports injury is carried out under the following conditions, and the image information is fused on the characteristic distribution of sports injury as follows:

$$\begin{cases} \dot{x}(t) = -Ax(t) + Wf(y(t-\sigma)), \\ \dot{y}(t) = -Cy(t) + Dx(t-\tau). \end{cases} \tag{1}$$

In the formula, A, W, C, and D represent the pixel collection points of the medical image of the sports injury site, it represents the pixel length and width of the injury site, and σ represents the neighborhood decomposition value of the sports injury information fusion. Using the single-frame vector feature decomposition method, the collected samples are divided into sports injury ultrasound medical images, and the kernel function of image detection is obtained:

$$f(y(t)) = [f_1(y_1(t)), f_2(y_2(t)), \cdots, f_n(y_n(t))]^T. \tag{2}$$

In the formula, f_n represents the proportion of the damaged part in the image pixels. The pixel feature distribution of the sports injury ultrasound medical image is obtained as follows:

$$k_z^g(t,\tau) = z\left(t + \frac{\tau}{2}\right) z^*\left(t - \frac{\tau}{2}\right). \tag{3}$$

In the formula, z represents the injury contour, t represents the edge segmentation parameter of the injury site, and τ represents the frame information of the ultrasound medical image. The feedback adjustment method is used to adjust the output stability of the ultrasound medical image of sports injury, and the feature quantity of the image edge contour satisfies

$$E\left[V(k)V^T(k)\right] = \begin{bmatrix} R_v^1(k) & D_{12}(k) & \cdots & D_{1N}(k) \\ D_{21}(k) & R_v^2(k) & \cdots & D_{2N}(k) \\ \vdots & \vdots & \ddots & \vdots \\ D_{N1}(k) & D_{N2}(k) & \cdots & R_v^N(k) \end{bmatrix}. \tag{4}$$

In (4), $R(k)$represents the adjustment parameter of the sports injury ultrasound medical image stabilization, and $D(k)$ represents the damage contour energy. The sports injury ultrasound medical images are carried out. In the ultrasound imaging environment, the sports injury information adaptive fusion of the sports injury ultrasound medical images is carried out, and the sports skeletal muscle block matching technology is used for the information enhancement processing of the sports injury ultrasound medical images, and the sports injury is obtained by combining the fuzzy information feature segmentation method. The distribution of edge contour and corner points of ultrasonic medical images is

$$R_V(k) = L(k)R(k)L^T(k). \tag{5}$$

In the formula, $R(k) = \mathrm{diag}\,\{r_1(k), r_2(k) \cdots, rNq(k)\}$ is the pixel intensity of the ultrasound medical image of sports injury. The fuzzy pixel feature extraction is performed of the damage ultrasound medical image, and the image enhancement result is obtained as follows:

$$\begin{aligned}\dot{V}_2(x(t)) = x^T(t)(R_1 + R_2)x(t) - x^T(t-h)R_1x(t-h) \\ - x^T(t-h_1)R_2x(t-h_1).\end{aligned} \quad (6)$$

In the formula, $x^T(t)$ represents the block matching feature of sports skeletal muscle, h_1 and h_2 represent the local injury feature extraction parameters, and R_1 and R_2 represent the ambiguity coefficient of sports injury ultrasound medical image. The image brightness components are fused, and the information fusion matrix $K(Z_1 + Z_2 + Z_3)^{-1}K^T$ and $L(Z_2 + Z_3)^{-1}L^T$ are obtained. $(t) < 0$; the image recognition of the damaged part is carried out, and the image recognition degree is obtained as

$$\psi(h_1, 0) = \psi + h_1K(Z_1 + Z_2 + Z_3)^{-1}K^T + h_2L(Z_2 + Z_3)^{-1}L^T < 0. \quad (7)$$

The sports injury point feature matching method is used to fuse and detect sports injury ultrasonic medical images, and the image features are extracted by the local feature detection method of the injury point, which improves the fusion ability of the image and increases the image recognition degree.

3.2. Measurement of the Segmentation Accuracy of Ultrasound Medical Images of Sports Injuries. Using the area weight analysis process, the scale decomposition of the ultrasound sports injuries is carried as

$$\begin{aligned}\left[I + PH^TR^{-1}H\right]^{-1}P = \left[P^{-1} + H^TR^{-1}H\right]^{-1} \\ = P - PH^T\left(HPH^T + R\right)^{-1}HP.\end{aligned} \quad (8)$$

In the formula, P is the gradient value of the ultrasound medical image of sports injury, H is the gray value of the ultrasound medical image of sports injury, and H^T is the spatial range of the ultrasound medical image of sports injury. The segmentation coefficient of sports injury ultrasound medical images is estimated according to the local variance, and the feature segmentation edge function is obtained as

$$\hat{y}(k|k-1) = Y(k|k-1)\hat{x}(k|k-1). \quad (9)$$

In the formula, k is the overall mean vector of sports injury ultrasound medical images, x is the resolution of the injury image, and Y is the total number of pixels at the injury site. Medical image is introduced into the fusion matrix of the segmentation, and the distribution of sports injury ultrasound medicine can be shown as

$$\hat{i}(k-1) = Y(k-1|k-1)\Phi^{-1}(k-1)J(k-1). \quad (10)$$

In the formula, Φ^{-1} represents the damage degree division function, and formula (10) is calculated, which can be expressed as

$$\max\left\{\sum_i \alpha_i K(x_i, x_i) - \sum_i\sum_j \alpha_{\alpha_j} K\left(x_i, x_j\right)\right\}, \quad (11)$$

which represents the quantitative feature reference value of the injury ultrasound medical image; $K(x_i, x_i) = 1$ indicates the adaptive weight of the injury ultrasound medical image. The deep convolutional neural network training method is used for the extracted sports injury points to automatically detect sports injury ultrasound medical images, and the convolutional neural network structure model for sports injury ultrasound is shown as

$$\frac{\partial L}{\partial R} = 0 \longrightarrow \sum_i \alpha_i = 1 \frac{\partial L}{\partial R} = 0 \longrightarrow \sum_i \alpha_i = 1. \quad (12)$$

Obtain the detailed texture of the source image, and satisfy $A - \alpha_i - \gamma_i = 0$; then, we have

$$d^2(x_i) = (x_i, x_i) - 2\sum \alpha_i\left(x_j, x_i\right). \quad (13)$$

In (13), x_i represents the abscissa detailed texture of the sports injury ultrasound medical image, and x_j represents the ordinate of the detail texture of the sports injury ultrasound video. According to the quality of fusion, the sports injury ultrasound is as follows:

$$\max 1 = \sum_i\sum_j \alpha_i\alpha_j K\left(x_i, x_j\right). \quad (14)$$

According to the interclass variance of the background image, it is performed to obtain calculation for the segmentation of the ultrasound medical image:

$$P(k|k) = \left[I - K(k)\breve{H}(k)\right]P(k|k-1). \quad (15)$$

Based on the above analysis, the use of CT features to conduct detailed of sports injury ultrasound medical images can improve the image detection accuracy and achieve sports injury ultrasound medical image segmentation.

3.3. Fuzzy Clustering Algorithm. The image segmentation area $J(U, V)$ is numerically equivalent to the fuzzy clustering weighted accumulation of the sum of the squares of the distances from the pixel point to the cluster center, namely [14],

$$J(U, V) = \sum_{k=1}^{N}\sum_{i=1}^{C}\left[u_i(x_k)\right]^{\lambda} d_{ik}^2. \quad (16)$$

In (16), U represents the membership set, $U = u_i(x_k)$; d_{ik} is the distance; $\mu_i(x_k)$ represents the membership and x_k is the*i*th. Let uA denote the set containing all membership types, A is a fuzzy set of pixels in X, and $uA(x)$ represents

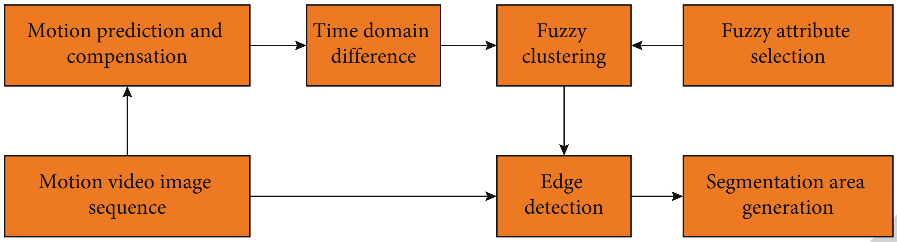

Figure 2: Sports image segmentation block diagram.

the membership value of the sample x. In the membership degree value, we can see what kind of segmentation region the sample x belongs to. When$uA(x) = 0$,$x$must not belong to fuzzy set$A$and when$uA(x) = 1$. In the membership value vs. image graph, the image segmentation operation correct fuzzy set and the appropriate membership function are determined, and the segmentation result error can be eliminated [15].

3.4. Sports Image Segmentation Method Based on Fuzzy Clustering Algorithm. The movement the sports image is relatively random, the image change trend is blurred, and area is not easy to determine. The proposed image segmentation method can divide the movement posture area [16].

The sports image playback state simultaneously starts the edge detection process, performs motion prediction and compensation image sequence, establishes the same background, and uses adjacent images [17]. It is extracted from the attributes of different frame values, and the fuzzy attributes of the target object in the process of motion are set, and the corresponding membership function is written. After that, its difference image is subjected to its process. The block diagram of image segmentation is shown in Figure 2 [18].

The following two issues need to be discussed: one is what attributes of the pose; it is that the attribute area cannot be the same and must have obvious difference. After discussion, it undergoes motion prediction and compensation, a small distance. The background of the sports image has a normal distribution, so it is a normal distribution [19].

The use of multiple images taken from different angles to restore the three-dimensional information of the scene of the technology is called multidimensional stereo vision, the current multidimensional stereoscopic vision algorithm does not consider some of the characteristics of the artificial object (e.g., building) itself, and the resulting three-dimensional point cloud is only determined by the matching of pixels between the multiangle images and the smoothness of the neighbor pixels, resulting in sparse, missing, or inconsistent point clouds generated in areas where the texture features are not obvious [20].

The file structure of indexed images is more complex, and in addition to the two-dimensional matrix that holds the image, it also includes a two-dimensional array called the color index matrix MAP. The size of the MAP is determined by the range of matrix elements in which the image is stored; if the matrix element range is [0,255], the size of the MAP matrix is 256X.3, which is expressed as

Table 1: Error comparison of sports injury ultrasound medical image segmentation.

Number of iterations	The method of this paper	CT segmentation	Wavelet segmentation
100	0.103	0.321	0.274
200	0.083	0.283	0.266
300	0.042	0.163	0.183
400	0.013	0.193	0.153
500	0.000	0.122	0.073

Table 2: Statistics of SA values.

Segmentation method	Segment 1	Segment 2
Iterations/time	0.0745	0.2112
Frequency domain segmentation	0.1234	0.2873
Time domain segmentation	0.1329	0.4237
Fuzzy clustering algorithm	0.2619	0.3324

MAP = [RGB]. The three elements of each row in the MAP specify the red, green, and blue monochrome values of the corresponding color of the row, and each row in the MAP corresponds to a gray value of the image matrix pixel; if the gray value of a pixel is 64, the pixel establishes a mapping relationship with the 64th row in the MAP, and the actual color of the pixel on the screen is determined by the [RGB] combination of the 64th row. That is, when the image is displayed on the screen, the color of each pixel is obtained by the gray value of the pixel stored in the matrix as the index by retrieving the color index matrix MAP [21]. The data type of the index image is generally 8-bit unsigned shape (int8), and the size of the corresponding index matrix MAP is 256X.3, so the general index image can only display 256 colors at the same time, but by changing the index matrix, the type of color can be adjusted. The data type of the index image can also be double. Indexed images are generally used to store images with relatively simple color requirements, such as Windows wallpapers with relatively simple color composition, which are more indexed image storage; if the color of the image is more complex, it is necessary to use RGB true color images [22].

In the detection algorithm of deep learning, the Faster RCNN algorithm is further optimized on the basis of the RCNN algorithm [23]. RCNN uses boxes, while Faster

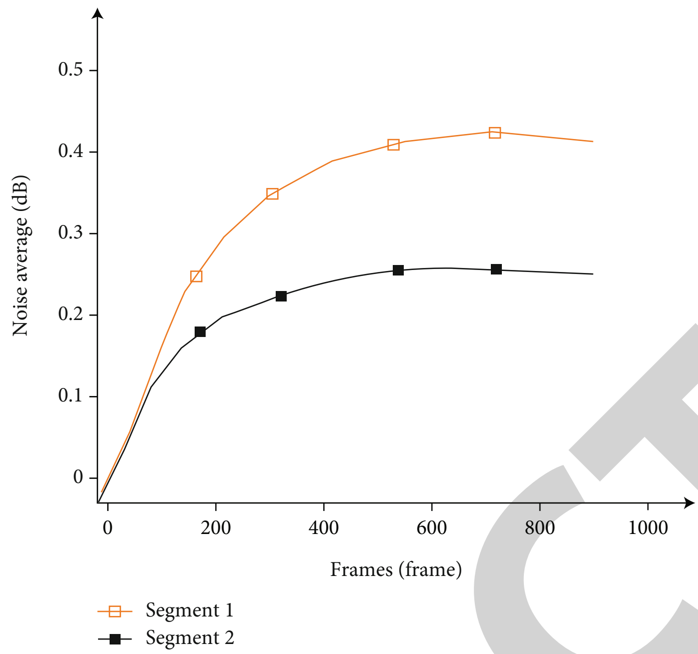

Figure 3: Image noise average curve.

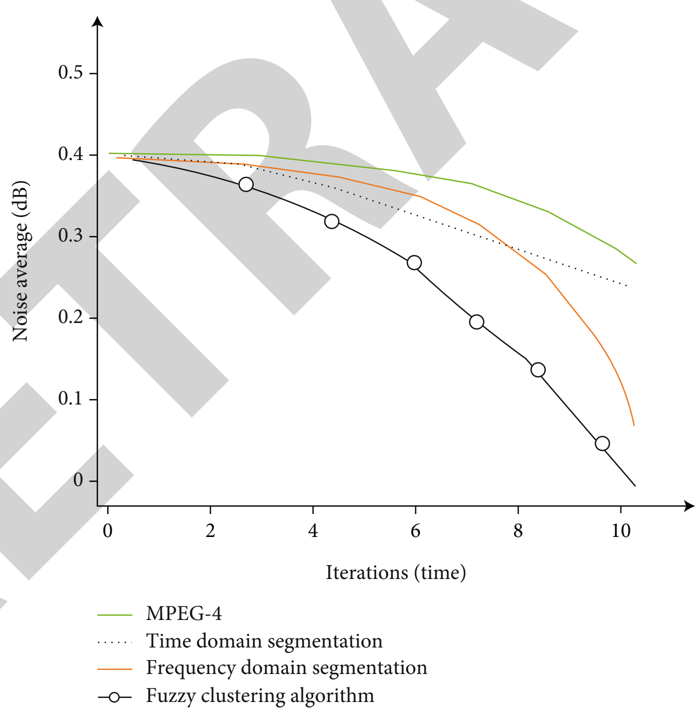

Figure 4: The curve of the relationship between the number of iterations and the average value of noise in segment 1.

RCNN does not use traditional sliding window and SS methods to generate detection boxes [24]. On the contrary, Faster RCNN replaces the selective search box with the regional proposal network structure to extract candidate boxes, which not only greatly improves the detection accuracy and detection speed but also basically achieves the purpose of real-time detection. The structure of the RPN network can be divided into two parts: one part [25, 26].

4. Result Analysis and Discussion

4.1. Integrated Learning Results and Analysis. This method can realize the segmentation of sports injury ultrasound medical images and has a high recognition degree of injury images. The error of the segmentation output of ultrasound medical images for sports injuries is shown in Table 1.

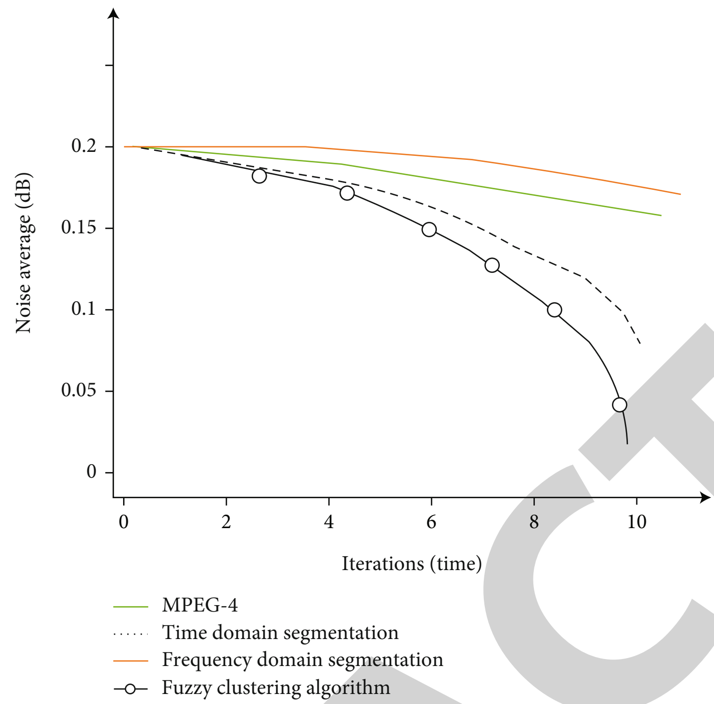

Figure 5: The curve of the relationship between the number of iterations and the noise average value in segment 2.

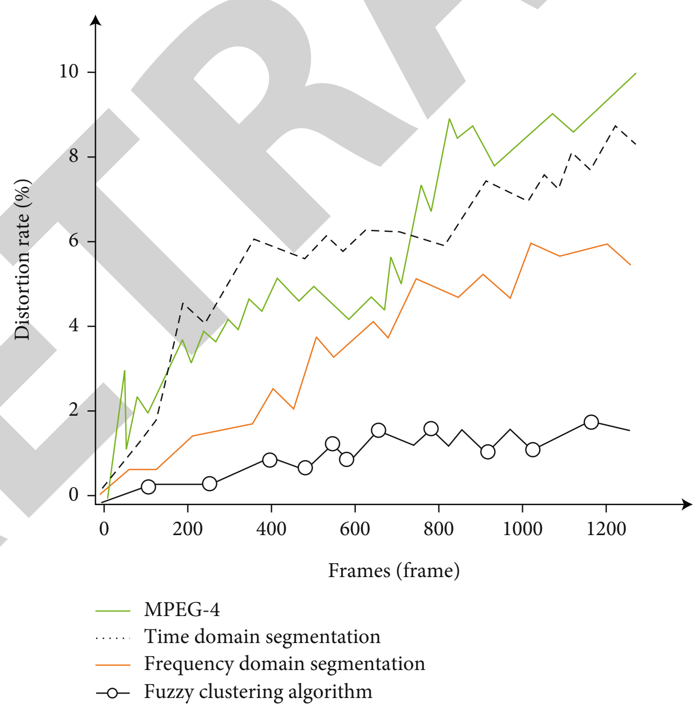

Figure 6: Spatial distortion rate variation in segment 1.

Analysis of Table 1 shows the number of iterations; the output errors of the three sports injury ultrasound medical image segmentation methods are gradually decreasing. The final error control of the CT segmentation method is 0.122, the final error control of the wavelet segmentation method is 0.073, and the error of the sports injury ultrasound medical image segmentation is reduced from 0.103 to 0.000, which can finally reach the effect of zero error. It can be an error for sports injury ultrasound medical image; the result is more accurate.

There are various forms of sports, and how to reduce the injury caused by sports is a current research hotspot. A

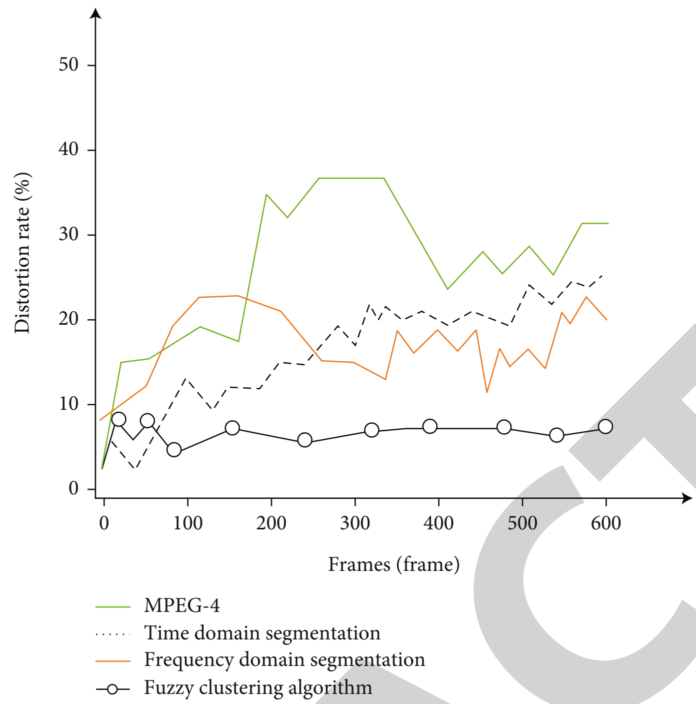

Figure 7: Spatial distortion rate variation in segment 2.

segmentation method of sports injury ultrasound medical images based on local features is used. A sports injury ultrasound and the CT feature are used to perform the transmission analysis of the sports injury ultrasound medical image feature detail, and the deep convolutional sports injury ultrasound medical image is used for the extracted sports injury points to achieve sports injury ultrasound medical image segmentation. Through the experimental analysis, it is known to have high precision for sports injury ultrasound medical image segmentation, high resolution and accuracy of sports injury point detection, and low error.

4.2. Fuzzy Clustering Experimental Results and Analysis. Two continuously changing images in 2016 for segmentation performed on each are as the following formula:

$$\mathrm{SA} = \frac{\sum_{(x,y)} M^{\mathrm{ext}}(x,y) \oplus M^{\mathrm{ref}}(x,y)}{\sum_{(x,y)} M^{\mathrm{ref}}(x,y)}. \quad (17)$$

The results of different methods are shown in Table 2. It is used in the smallest SA value among the image segmentation area. Accurately segment images with complex factors.

The method needs to perform image segmentation to obtain it. This for the noise of method is fast. Figure 3 is the average noise curve of two sports images, Figures 4 and 5 are the relationship curves and the mean value of noise for it. In Figure 3, the noise of it is changing, and the overall rising trend of the noise is gentle. In Figures 4 and 5, the image noise is reduced after it. The method based on the fuzzy can perform fast. In iteration 6, it can reduce the image noise to 50% of the original.

Figures 6 and 7 are, respectively, the variation of spatial distortion rate during the methods of two continuously changing moving images. The definition of it is as follows:

$$d_n = \frac{\sum_{(x,y)} O^{\mathrm{ext}}(x,y) \oplus O^{\mathrm{ref}}(x,y)}{\sum_{(x,y)} O^{\mathrm{ref}}(x,y)} \times 100\%. \quad (18)$$

In the formula: d_n represents the nth; O^{ext} and O^{ref} represent the split pixel (x, y) value. It can be seen from Figures 6 and 7. The segment 1 image has a large number of frames. The spatial distortion rate of the fuzzy clustering algorithm in the two images is relatively stable, and the value is low, which means that the fuzzy clustering algorithm reduces the noise of the segmentation image and obtains a clear moving target. Trend. The other obtained segmentation images are relatively blurry.

5. Conclusion

The method in this paper has not conducted in-depth analysis on the processing time of sports injury ultrasound medical image segmentation. It is necessary to further shorten the identification time of the damaged part of sports injury images, improve the identification ability, and optimize sports injury ultrasound medicine. Image segmentation technology improves the breadth and effectiveness of clinical applications and increases the value of practical applications. The method based on fuzzy clustering algorithm can improve sports images. Compared with other methods, this method has better spatial accuracy performance. The experimental evaluation of the distortion rate is in the leading position. The application of this analysis method will have movement skills characteristics of fit people through it. The focus is on sports and so on. By comparing the experimental methods, the validity of the deep learning API-MASK workpiece detection algorithm used in the intelligent detection of sports is verified and analyzed. With the acceleration of the intelligent process, the following issues need to be further studied in practical applications: (1) the number of images in the test image set and the experimental image set in this paper is relatively small, which has a certain impact on the detection accuracy of the API-MASK workpiece detection algorithm in this paper. On this basis, the image acquisition of the target workpiece is increased to improve the detection rate. (2) Due to the limited experimental conditions and experimental time, the existing machine vision system has certain limitations on the size of the workpiece and the number of workpiece detection. In order to improve the detection accuracy of the workpiece, the image acquisition system and the structural design of the acquisition system should be further studied for the acquisition of three-dimensional images, so as to meet the intelligent, flexible, and highly integrated intelligent manufacturing and provide the basis for future intelligent grasping. The simulation results show that this method has high accuracy for sports injury ultrasound medical image segmentation, the error value can be controlled below 0.103, and finally, the effect of zero error is achieved. It is confirmed that the method proposed in this paper has high resolution and accuracy for sports injury point detection and has strong practical application ability.

Data Availability

The figures and tables used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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