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Sport injury imaging for deep blood flow distribution with laser speckle

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Abstract

INTRODUCTION: When laser speckle program technology is used to measure the blood flow distribution of deep tissues (such as subcutaneous tissue) in sports injuries, the deep blood flow characteristics of sports injuries contain a large amount of turbid tissue fluid. Laser passing through turbid tissue fluid will produce strong interference static speckle, masking the dynamic speckle of blood flow distribution, resulting in poor imaging effect of blood flow characteristics.
OBJECTIVES: In order to solve the problem of poor imaging performance of deep tissue blood flow distribution in sports injuries, laser speckle imaging optimization technology is proposed and applied to the measurement of deep tissue blood flow distribution in sports injuries.
METHODS: Based on the principle of laser speckle imaging technology, the problems in laser speckle imaging of deep blood flow distribution characteristics in sports injuries are analyzed. An exponential Laplace loss function is introduced to reduce the amplitude of changes in blood flow characteristics in intra class sports injuries and collect deep blood flow distribution characteristics in sports injuries; On the basis of calculating the laser speckle contrast ratio, the blood volume flow rate is determined, and the blood volume flow rate data is combined with the laser speckle contrast ratio to achieve imaging of deep blood flow distribution in sports injuries.
RESULTS: The experimental results show that the improved laser speckle imaging technology has better imaging effects in imaging the deep blood flow distribution of sports injuries; Compared with the comparison method, the DICE coefficient, average accuracy MPA, and global imaging index have all improved to 0.93, 0.96 and 0.97 respectively, and has a short imaging time to 3.103s.
CONCLUSION: This method can effectively improve the imaging effect of images and is feasible.

Keywords: Sports injury; Laser speckle; Deep; Blood flow characteristics; Loss function; Contrast ratio; Imaging

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1. Introduction

Laser speckle phenomenon refers to the random distribution and movement of scatters when laser is irradiated on a rough surface or inside a medium, resulting in scattered light exhibiting a randomly distributed speckle pattern in space and time [1]. In recent years, with the continuous progress of optical technology, laser speckle technology has been widely applied in fields such as blood flow detection and tissue perfusion evaluation. Laser Speckle Contrast Imaging (LSCI), as a non-invasive and real-time blood flow imaging technology, can reflect the internal blood flow situation of tissues by measuring the dynamic changes of speckle patterns [2,3]. However, traditional LSCI technology mainly focuses on the detection of surface blood flow, and still faces many challenges in imaging the blood flow distribution of deep tissues. Therefore, how to achieve effective detection of deep blood flow distribution while ensuring imaging accuracy has become an urgent problem in the field of laser speckle blood flow imaging.

Related researchers have conducted research on this issue. Reference [4] proposes a color camera combined with non rigid registration algorithms to simultaneously image tissue structure and laser speckle, aiming to improve the motion correction ability of speckle imaging. Previous studies have attempted to use both original speckle images and rigid registration algorithms for global misalignment, but it is difficult to correct local non rigid motion using only granular original speckle images, especially in tissues dominated by small blood vessels, which leads to limitations. However, the imaging effect of deep blood flow distribution with sports injuries is poor and not suitable for large-scale use. Reference [5] proposed a multi exposure laser speckle contrast imaging (EGNNN-BFVP MeLSCI) blood flow velocity prediction method based on evolutionary gravity neurotron neural network. Initially, the input MeLSCI dataset was collected from the real-time dataset. The input image is enhanced and denoised using the Variable Phase Maintaining Dynamic Range Compression (APPDRC) preprocessing technique. The preprocessed image is extracted using a feature extraction method that relies on the Gray Level Co occurrence Matrix (GLCM) window adaptive method. The GLCM window adaptive method was used to retrieve the grayscale information, image derivatives, geodesic information, contrast, energy, correlation, uniformity, entropy and other features of the image. Then, the extracted features are transformed into an EGNNN classifier to achieve accurate prediction of blood flow velocity. The performance of the proposed method was tested on the Python platform. However, there is a problem of poor imaging effect when imaging the deep blood flow distribution in sports injuries.

Reference [6] proposes an image registration algorithm to eliminate image jitter and improve the resolution of small blood vessels, addressing the issue of speckle images captured in live experiments due to factors such as animal respiration and heartbeat [7]. In addition, due to the time-consuming computation of the original algorithm, this article analyzes the algorithm and writes a parallel computing program to improve the computational speed to meet the needs of clinical real-time monitoring [8]. However, when imaging the deep blood flow distribution of sports injuries, the problem of overlapping feature clusters was not considered, resulting in confusion and mis-judgment of blood flow distribution characteristics. Reference [9] proposes a cerebral blood flow analysis method based on Laser Speckle Contrast Imaging (LSCI) technology to confirm the flow of blood flow and cerebral blood perfusion after vascular anastomosis. Firstly, build an LSCI system to collect speckle images, perform improved time contrast analysis and pseudo color processing on it, and obtain blood flow velocity images to monitor changes in flow velocity. Secondly, manually selecting the benchmark points of the region of interest can capture the region of interest. After preprocessing, the improved Canny algorithm is used to extract the edge lines of blood vessels and calculate their diameters. Finally, the reliability of the LSCI system in monitoring blood flow velocity changes and measuring vascular diameter was verified through animal experiments. However, when imaging the deep blood flow distribution of sports injuries, the problem of excessive changes in the deep blood flow characteristics caused by interference with static speckle was not considered, resulting in poor imaging results of the final blood flow distribution.

In order to solve the problems in the above methods and improve the imaging effect of deep blood flow distribution in sports injuries, an improved laser speckle imaging technology is proposed and designed. By introducing an exponential Laplace loss function, the variation amplitude of deep blood flow characteristics in intra class sports injuries is reduced, and the distribution characteristics of deep blood flow in sports injuries are collected; On the basis of calculating the laser speckle contrast ratio, the blood volume flow rate is determined, and the blood volume flow data is combined with the laser speckle contrast ratio to achieve imaging of deep blood flow distribution in sports injuries and solve the problem of static speckle interference in internal tissue fluids.

2. The interference problem of laser speckle in the study of blood flow distribution in sports injuries

Since the invention of laser, the phenomenon of laser speckle has been widely studied [10-11]. When laser is irradiated on the surface of an object, scattered light passing through different optical paths interferes with each other, forming an image called laser speckle image. This type of image contains a larger amount of information about the irradiated object, and its value is higher. Laser speckle imaging technology is an optical imaging method that utilizes a large amount of information about the illuminated object contained in laser speckle images to analyze and study various properties and features of the object [12-13]. Given the above characteristics of this technology, its application in the recognition of deep blood flow distribution characteristics in sports injuries provides more accurate and reliable medical data support for relevant personnel.

Laser speckle imaging [14] is an integrated technology that utilizes the principle of laser speckle and consists of an image acquisition module and an optical image processing module. This technology generally uses laser as the light source. At the same time, in order to improve image quality, the laser source is attenuated and expanded to make its illumination distribution more uniform. The acquisition of blood flow distribution characteristics images is achieved by converting image signals into digital signals through a camera, which facilitates subsequent analysis and processing. The recognition imaging system of this technology is shown in Figure 1.

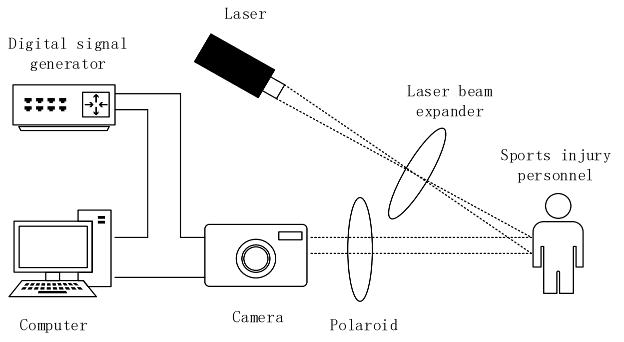

Figure 1. Laser speckle imaging for identifying blood flow distribution characteristics in sports injuries

Based on the content of Figure 1, we have gained a deeper understanding of the composition and working principle of the laser speckle imaging system for deep blood flow distribution characteristics in sports injuries. This system mainly consists of key components such as laser, laser beam expander, digital signal generator, polarizer, camera, and computer, which work together to achieve accurate imaging of deep blood flow distribution characteristics in sports injuries.

In Figure 1, the laser is a light source, provides a coherent beam for generating laser speckle patterns. The high coherence and monochromaticity of laser are the key to the formation of clear speckle patterns.

The laser beam expander expands the diameter of the laser beam, so that the laser spot more evenly covers the area to be measured, reduces the diffraction effect of the edge of the spot, so as to improve the uniformity and quality of imaging.

The digital signal generator controls the switching and pulse mode of the laser to ensure that the laser emits the laser according to a predetermined time series in order to synchronize with the camera's image acquisition.

The polarizer adjusts the polarization state of the laser beam to help filter out unpolarized light and improves the signal-to-noise ratio of the imaging system, and the camera captures laser speckle patterns and convert optical signals into digital signals.

The computer is used to receive and process digital image signals captured by cameras. Software running on the computer can process, analyze and display images, extract blood flow distribution characteristics, and store data for further study.

Laser speckle imaging technology plays a crucial role in the research and diagnosis of sports injuries. In order to extract effective features from complex images, it is necessary to ensure the acquisition of high-quality motion injury images. Firstly, it is required that the image has a relatively uniform brightness distribution to reduce the interference of noise on the imaging results. At the same time, in order to ensure the reusability and flexibility of the imaging system, it is necessary to ensure that the trigger frequency of the camera is adjustable to meet the imaging needs in different scenes.

In order to facilitate the reliability of collecting deep blood flow distribution characteristics of subsequent sports injuries, it is also necessary to consider the storage method of sports injury images. By manually setting the storage method, the format, resolution, and storage location of the saved image can be flexibly selected according to research needs. But sports injuries are often accompanied by severe swelling behavior, and these swollen tissue fluids bring great interference to normal speckle. When laser speckle program technology is used to measure the blood flow distribution of deep tissues (such as subcutaneous) in sports injuries, the large amount of turbid tissue fluid contained in the deep blood flow characteristics of sports injuries can have adverse effects on the imaging results. When the laser passes through these turbid tissue fluids, it will generate strong interference static speckle, causing significant intra class changes in the imaging method, affecting the acquisition results of deep blood flow distribution characteristics in sports injuries, and also leading to dynamic speckle that masks blood flow distribution, resulting in poor imaging results of blood flow distribution. To solve this problem, it is necessary to conduct in-depth research on the interaction mechanism between laser and turbid tissue fluid, achieving more comprehensive and accurate detection of deep blood flow distribution in sports injuries.

3. Collection of deep blood flow distribution characteristics in sports injuries

Based on the analysis of the interference problem of laser speckle in the study of blood flow distribution in sports injuries mentioned above, in order to avoid the impact of large intra class changes caused by interference with static speckle on the collection of deep blood flow distribution characteristics in 2ction to reduce the amplitude of changes in deep blood flow distribution characteristics in intra class sports injuries, adjust the distance between features of different centers, optimize the process of collecting deep blood flow distribution characteristics in sports injuries, making the extracted features reflect the actual blood flow changes more accurately, and thus improve the subsequent imaging effect. Set it as the loss function L_c and define it as follows:

$$L_c = \frac{1}{2}\sum_{i=1}^{k}\left\| x_a - c_{y_a} \right\|^2 \tag{1}$$

In the formula, x_a represent the speckle imaging feature vectors of the deep blood flow distribution of the motion injury obtained by the a-th object, c_{y_a} represents the center of the y_a laser speckle imaging vector, and k represents the total amount in the clustering process.

When backpropagating laser speckle mapping data, calculate the center of the partial derivative of x_a:

$$\frac{L_c}{x_a} = x_a - c_{y_a} \tag{2}$$

Update cluster centers during iteration:

$$\Delta c_i = \frac{\sum_{i=1}^{k} \delta(y_a, i) \times (x_a - c_{y_a})}{1 + \sum_{i=1}^{k} \delta(y_a, i)} \tag{3}$$

In the formula, $\delta(y_a, i)$ is the indicator function, defined as $\delta(y_a, i) = \begin{cases} 1, y_a = i \\ 0, y_a \neq i \end{cases}$. To fully utilize the speckle information of deep blood flow distribution characteristics in sports injuries from multiple datasets, if the distance between image samples and other clustering centers is set to L_{MT}, then:

$$L_{MT} = -\sum_{i=1}^{k} \Delta c_i \frac{\exp\left(-\frac{1}{2}\left\|x_a - c_{y_a}\right\|^2 - \lambda\right)}{\sum_{j=1, j\neq i}^{k} \exp\left(-\left\|x_a - c_{y_a}\right\|^2\right)} \tag{4}$$

In the formula, λ represents the boundary parameters of the laser speckle image.

To reduce the computational cost of laser speckle imaging and thus reduce imaging time, the random gradient descent method is used to update the distance parameter between image samples and other cluster centers [15,16]. The optimized formula is:

$$L'_{MT} = -\sum_{i=1}^{k} \Delta c_i \frac{\exp\left(-\left\|x_a - c_{y_a}\right\|^2 - \lambda\right)}{\sum_{j=1, j\neq i}^{p} \exp\left(-\frac{1}{p}\left\|x_a - c_{y_a}\right\|^2\right)} \tag{5}$$

In the formula, p represents the parameter of the motion injury image, which can make the calculation skip class centers that are far from the current center. Finally, the loss function of laser speckle imaging is calculated through the L_{MT}-value of multiple datasets [17], in order to adjust the distance between features of different class centers, avoid the impact of large intra class changes caused by interference with static speckle on the collection of deep blood flow distribution features of motion injuries, and make it easier to distinguish features of different categories, completing the collection of deep blood flow distribution features of motion injuries. The expression is:

$$L_i = -\frac{1}{N} \sum_{i=1}^{N} \lambda_i L'_{MTi} \tag{6}$$

where, N represents the number of laser speckle images, and λ_i represents the boundary parameters of the i-th laser speckle image.

In summary, the proposed method introduced the exponential Laplace loss function and adopted the stochastic gradient descent to adjust the distance between image samples and the clustering center features, thereby improving the extraction ability of the model for the deep blood flow of the sports injury and making the extracted features more accurately reflect the actual blood flow changes. According to the collected blood flow distribution, the influence of static speckle interference on the collected feature recognition is reduced.

Under static speckle interference, laser speckle contrast ratio analysis is carried out in this paper. In order to improve imaging accuracy and reliability, blood volume flow is calculated and combined with laser speckle contrast degree, identifying the deep blood flow distribution in sports injury under static speckle interference in this paper. Therefore, deep blood flow distribution imaging is realized.

4. Imaging method of deep blood flow distribution in sports injuries based on laser speckle imaging

However, static speckle interference not only leads to significant intra class changes in imaging methods, but also makes it difficult to grasp the dispersion of deep blood flow distribution characteristics of various sports injuries in clustering, ignoring the possibility of overlapping clusters, resulting in confusion and misjudgment of blood flow distribution characteristics. Therefore, determining the laser speckle contrast ratio, calculating the blood volume flow, and combining the blood volume flow data with the laser speckle contrast ratio, based on the collected deep blood flow distribution characteristics of sports injuries, to complete the recognition of deep blood flow distribution characteristics of sports injuries under static speckle interference, solve the problem of cluster overlap, and thus achieve deep blood flow distribution imaging.

4.1. Analysis of laser speckle contrast ratio

In practical measurements, scattered light usually includes two parts: static scattering and dynamic scattering [18,19]. The existence of static scattering has different effects on spatial contrast analysis and temporal contrast analysis. In the process of spatial contrast analysis, static scattering can lead to a lower estimated flow velocity; In time contrast analysis, static scattering only adds a scaling factor when estimating flow velocity and does not affect the measurement of relative flow velocity changes.

The dynamic scattering results in the change of speckle pattern with time, which reflect the motion state of scattered particles. However, the motion speed of the scattered particles is slow relative to the frequency of the laser. Also, since the coherence length of the laser is usually long, the scattered light still maintains a certain degree of coherence in movement of the scattered particles, which makes the dynamic scattering have less influence on the laser speckle contrast degree. Therefore, in the subsequent analysis, only the ratio of dynamically scattered electric field to dynamically scattered light should be considered.

Therefore, when using speckle contrast to study the motion of scattered particles, it is necessary to fully consider the influence of static scattering on spatial speckle contrast.

For the presence of static scattering, the electric field generated by scattered light can be expressed as:

$$E(t)=E_f(t)e^{-i\omega t}+E_s e^{-i\omega t} \tag{7}$$

where, $E_f(t)$ and E_s represent the electric fields of dynamic scattering and static scattering light, respectively, and w represents the angular frequency of the electric field, and t is the time. The correlation function expression of speckle intensity [20-21] is obtained by integrating the second-order moment of light intensity within time using the Siegert relationship:

$$g(\tau)=1+\beta\left[\rho^2\left|g_1(\tau)^2\right|+2\rho(1-\rho)\left|g_1(\tau)\right|+(1-\rho)^2\right]+v_n \tag{8}$$

where, ρ represents the proportion of dynamic scattered light to the total scattered light, v_n represents the noise during the actual measurement process, $g_1(\tau)$ represents the electric field auto-correlation function, τ represents the correlation time of light intensity fluctuations, and β is a constant factor.

Due to the presence of a large amount of turbid tissue fluid in the deep blood flow characteristics of sports injuries, laser scattered particles passing through the turbid tissue fluid will produce interference static speckle, making it difficult to accurately estimate the movement of scattered particles, resulting in the inability to grasp the dispersion of deep blood flow distribution characteristics of various sports injuries in the clustering. This ignores the possibility of overlapping in the clustering, leads to bias in the results obtained when identifying deep blood flow distribution of sports injuries, which affects the final imaging effect of deep blood flow distribution. Therefore, fully considering the influence of static scattering on speckle contrast, based on the results of formulas (7) and (8) above, the laser speckle correlation contrast is obtained, and the expression for the correlation contrast is as follows:

$$K_t^2=\left[\beta\rho^2\frac{e^{-2x}-1+2E(t)}{2x^2}+4\beta g(\tau)(1-\rho)\frac{e^{-x}-1+E(t)}{x^2}\right]+v_n \tag{9}$$

In the formula, x represents the ratio of camera exposure time to correlation time, and e^{-x} represents the standard error function. Thus, by accurately estimating the motion changes of scattered particles through laser speckle contrast, the blood flow status at the site of sports injury can be evaluated. Next, the blood volume flow rate is determined to understand the blood supply situation at the injury site. Based on this, combined with laser speckle contrast ratio, the dynamic and static characteristics of blood flow are described more comprehensively (laser speckle contrast ratio is a dynamic characteristic, and blood volume flow data is a static characteristic). The deep blood flow distribution characteristics of sports injuries are more accurately identified, and the confusion and misjudgment of blood flow distribution characteristics caused by cluster overlap are solved, improving the accuracy of deep blood flow distribution imaging.

4.2. Deep blood flow distribution imaging method

After determining the contrast ratio, for the same flow velocity region, the more pixels the square window contains, the smaller the statistical noise, and the more accurate the estimated blood flow velocity in that region; However, in actual measurements, due to the existence of static scattering, it interferes with the speckle contrast., resulting in inaccurate estimation of blood flow velocity and inability to accurately identify the blood flow distribution characteristics in the motion injury area. To improve the accuracy and reliability of imaging, it is necessary to determine the volume flow rate of blood in order to correct the interference of scattered particle motion in the pipeline on speckle contrast and affect blood flow distribution. Generally speaking, the spatial velocity distribution of the solution inside the pipeline is constant, and the flow model inside the pipeline can be represented as:

$$v(r)=v_{\max}\left(1-4a\frac{r^m}{d^m}\right) \tag{10}$$

In the formula, $v_{\max}$ represents the maximum center line velocity inside the pipeline, d represents the diameter of the pipeline, a represents the proportional factor of non-zero velocity on the inner wall of the pipeline, r represents the distance from the center line, and m represents the bluntness of the flow curve.

Assuming that the flow model inside the pipeline approximates a parabola, i.e. $m=2$, the average velocity of the solution inside the pipeline can be expressed as:

$$v_{aver} = \frac{8}{d^2}\int_0^{d/2} v(r)\,dr = \left(1\frac{a}{2}\right)v_{\max} \quad (11)$$

The volumetric flow rate can be obtained by multiplying the average velocity by the cross-sectional area of the pipeline:

$$F = \frac{1}{4}\left(1-\frac{a}{2}\right)\pi d^2 v_{aver} \quad (12)$$

For the convenience of calculation, this article assumes that the value of a for pipes with different inner diameters is the same. Therefore, the volume flow rate inside the pipe is directly proportional to the product of the closing time and the pipe diameter.

Combining blood volume flow data with laser speckle contrast ratio, based on the collected deep blood flow distribution characteristics of sports injuries, to complete the recognition of deep blood flow distribution characteristics under static speckle interference and achieve imaging of deep blood flow distribution. During the recognition process, the information of the same problem is shared in different regions, so that laser speckle imaging has the same task data during the recognition process. Then, adaptive block labeling is used to process the target area of deep blood flow distribution characteristics in sports injuries, and feature recognition images are obtained:

$$F(x,y) = \sum_{i=1}^{n_r}\sum_{j=1}^{n_x}\frac{FW^{ij}(x,y)\cdot O^{ij}(x,y)\cdot L_i}{K_t^2} \quad (13)$$

where, $O^{ij}(x,y)$ represents the extracted set of laser speckle image feature points, and $W^{ij}(x,y)$ represents the iterative function, n_r represents the number of features extracted from the laser speckle image, and n_x represents the number of iterations.

Based on the above information, obtain the information of the target edge contour points for the deep blood flow distribution characteristics of sports injuries:

$$S_t = \left\{ s_t^i\left(F(x,y)\right); i = 1,2,\cdots,n_r \right\} \quad (14)$$

where, s_t^i denotes the spatial position of feature edge points in i-th laser speckle image during time t. By using template matching method to segment the feature target area of deep blood flow speckle images in sports injuries, corner laser speckle scanning results are obtained:

$$\begin{cases} p_{th}^{(b_{\text{int}})} = C_t \sum_{x_i \in w} o\left(\|x_i\|^2\right)\delta\left(h(x_i) - b_{\text{int}}\right)S_t \\ p_{te}^{(b_{\text{in}e})} = C_t \sum_{x_i \in w} o\left(\|x_i\|^2\right)\delta\left(v_{xi} - b_{ine}\right)S_t \end{cases} \quad (15)$$

where, $C_t = \dfrac{1}{\sum_{x_i \in w} k\left(\|x_i\|^2\right)}$ represents the contrast parameter of the speckle pattern at time t, w is the feature target area of the deep blood speckle with sports injury, x_i is the pixel position of the i-th feature sampling in the image, $h(x_i)$ is the edge detection filter output at the position x_i, b_{int} is the background intensity, b_{ine} is the background illumination intensity of the deep blood speckle image, δ is the incremental coefficient, v_{xi} represents the blood flow velocity component at the position x_i, o represents the sampling number, $p_{th}^{(b_{\text{int}})}$ and $p_{te}^{(b_{\text{in}e})}$ represents the laser speckle scanning results of the sports injury deep blood speckle image feature target.

Through laser speckle imaging recognition, the target is separated from the deep blood flow distribution characteristics of the entire sports injury, and the target pixels near the sub correlation coefficient $\hat{X}\left(p_{th}^{(b_{\text{int}})} \middle| p_{te}^{(b_{\text{in}e})}\right)$ are extracted as follows:

$$X_k = f_k\left(\hat{X}\left(p_{th}^{(b_{\text{int}})} \middle| p_{te}^{(b_{\text{in}e})}\right)\right) + f_X(k)\left[\overline{X} - \hat{X}\left(p_{th}^{(b_{\text{int}})} \middle| p_{te}^{(b_{\text{in}e})}\right)\right] + V_k O^{ij}(x,y) \quad (16)$$

where, V_k represents the extraction coefficient, and $\overline{X}$ represents the mean of the sub correlation coefficients, f_o is the brightness value of the sampling point o, $f_X(k)$ is the probability. By using Equation (17), the predicted value of $o+1$ sampling points for detecting the feature target X_{o+1} in laser speckle image can be obtained as follows:

$$\begin{aligned} \hat{X}_{o+1} &= Q\left[X_{o+1} \middle| o\right] \\ &= Q\left[f_o\left(o, \hat{X}\left(p_{th}^{(b_{\text{int}})} \middle| p_{te}^{(b_{\text{in}e})}\right)\right) + f_X(k)\left[X_k - \hat{X}\left(p_{th}^{(b_{\text{int}})} \middle| p_{te}^{(b_{\text{in}e})}\right)\right] + V_k O^{ij}(x,y)\right] \end{aligned} \quad (17)$$

where Q is the expectation operator.

Under the improved laser speckle imaging technology, the imaging estimation of the target area for deep blood flow distribution characteristics in sports injuries is as follows:

$$H = \hat{X}_{o+1} + \hat{X}' \quad (18)$$

In the formula, $\hat{X}'$ represents the estimation error term of the target area for the deep blood flow distribution characteristics of sports injuries. At this point, the imaging method for deep blood flow distribution in laser speckle motion injuries is designed.

Firstly, according to the principle of laser speckle imaging, the laser speckle imaging of deep blood flow distribution in sports injury is analyzed.

Secondly, the intense interference of static speckle by laser passing through turbiditic tissue fluid causes excessive intra-class changes, which affects the extraction of the deep blood flow distribution features. In order to solve this problem, the exponential Laplace loss function is introduced and the inverse propagation method is adopted to adjust the distance between the features of the class clustering center, so as to accurately reflect the actual blood flow changes.

Finally, considering the static speckle interference, the laser speckle contrast degree is calculated, and the blood volume flow is determined. Then, laser speckle contrast degree are combined to realize the imaging of deep blood flow distribution in sports injury.

5. Experiments and Results

To verify the effectiveness of the laser speckle imaging technology designed for deep blood flow distribution in sports injuries, and to test and analyze its application effects.

5.1. Experimental preparation

The experiment takes a sports injury patient from a hospital in a certain city as the research object, and randomly selects a finger injury patient from the hospital. The blood flow distribution characteristics of the sports injury imaging are compared and analyzed using the method proposed in this paper, compared with the non-rigid registration method, evolutionary gravity neural network method, and image registration method. Here, each method describes the realization process of blood flow distribution of sports injury, as shown in Table 1 below.

Table 1. Detailed Process of Different Methods

Method	Implementation Processing
The proposed method	Exponential Laplace loss + stochastic gradient descent: Extraction of blood flow distribution; Laser speckle contrast degree + blood volume flow: imaging of deep blood flow distribution .
The non-rigid registration method	Color camera takes tissue structure and laser speckle images; Non-rigid registration + motion correction: decrement of distortion caused by tissue movement.
Evolutionary gravity neocognitron neural network	The phase preserving dynamic Range compression (APPDRC): enhance and denoise the input image; GLCM window adaptive method: retrieve the image features; Evolutionary gravity neocognitron neural network (EGNNN) classifier: imaging of deep blood flow distribution in sports injury.
The image registration method	Image registration: register the speckle image to complete the imaging of the deep blood flow distribution in the sports injury.

The equipment used in the experiment mainly includes computers, lasers, laser beam expanders, etc. The main equipment parameters are shown in Table 2.

Table. 2 Experimental equipment parameters

Device Name	Parameter Name	Parameter
Computer	Model	YPC-820
	Processor	Intel® CoRE ™i7
	Memory	8G
Laser	Model	LR-ILN-1870 (Red light)
	Wavelength	1870±20nm
	Power	1~800mW (Adjustable)
	Spot mode	TE00
	Beam size	5.0 x 5.0mm
Laser beam expanding mirror	Model	VEX13
	Wavelength	240~2000nm
	Magnification factor	1~3
	Directional stability	＜0.5mrad
	Total output	97%
signal generator	Model	33611A
	sampling rate	660 MSa/s
	resolving power	14 bit

Under the improved laser speckle imaging, the motion injury recognition method set the time interval of data collection on the computer, and determine the number of images according to the collection time, then controls the time interval and quantity of collecting deep blood flow distribution feature images of motion injuries, provides accurate data for subsequent image processing and sports injury recognition.

The time interval is set to 100ms and the collection duration is 1s. Thus, the laser is connected with the laser beam expanding mirror to ensure that the laser beam can shine evenly on the surface of the tissue. The signal generator is then connected to the laser in order to control the switching and pulse mode of the laser. The camera equipment is connected with the computer to capture the laser speckle pattern according to the set extraction interval and time. Finally, the collected speckle image is sent to the computer for use.

The experimental scene is shown in Figure 2:

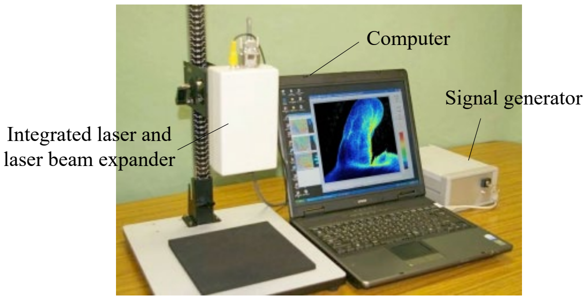

Figure 2. Experimental Scene Diagram

5.2. Experimental indicators

To verify the impact of the improved method on the imaging results of blood flow distribution, a comparative experimental study was conducted using DICE coefficient, average accuracy MPA, and global imaging index as evaluation indicators.

(1) The DICE coefficient is used to measure the degree of overlap between imaging results and actual target results. The range of values is between 0 and 1, and the closer the value is to 1, the better the detection performance.

$$DICE = 2\frac{i \cap j}{i \cup j} \tag{19}$$

In the formula, i represents the actual result; j represents the detection result.

(2) Average accuracy is used to measure imaging accuracy, with a range of values between 0 and 1. The closer the value is to 1, the better the imaging effect of the shunt distribution.

$$MPA = \frac{1}{k}\sum_{u=1}^{k}\frac{p_u}{\sum_{u=0}^{k} p_j^u} \tag{20}$$

In the formula, k represents the total number of categories; p_j^u represents the number of blood vessels in the u-th category; p_u represents the number of correctly imaged images in the u-th category.

(3) Global detection index GPI_j: Taking into account multiple key parameters and factors, it mainly measures the overall imaging effect. The higher the index, the better the imaging effect.

$$GPI_j = \sum_{k=0}^{3} \alpha_k \left(z_{jk} - z_k\right) \tag{21}$$

where, α_k represents the value of the determination coefficient when it is the same as the number of categories k; z_{jk} represents the j-th imaging accuracy when the number of categories is k; z_k represents the imaging accuracy when the number of categories is k.

(4) Imaging spent time T: The total time spent, which can effectively measure the imaging efficiency. The shorter time means the higher imaging efficiency, which can effectively shorten the imaging time and improve the efficiency and practicability of the imaging method of deep blood flow distribution.

5.3. Analysis of experimental results

Due to the different effects of static scattering on spatial and temporal contrast analysis, in order to present its effects, the contrast values of space and time under different image pixels in static scattering are shown in Figure 3.

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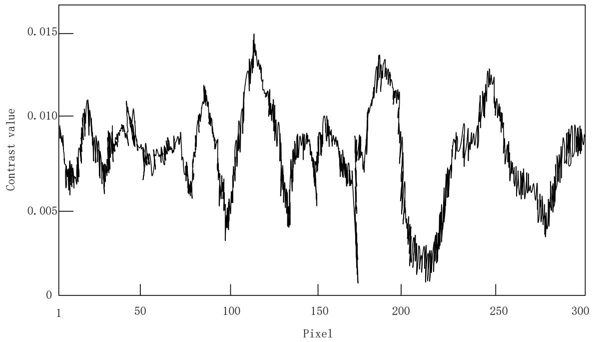
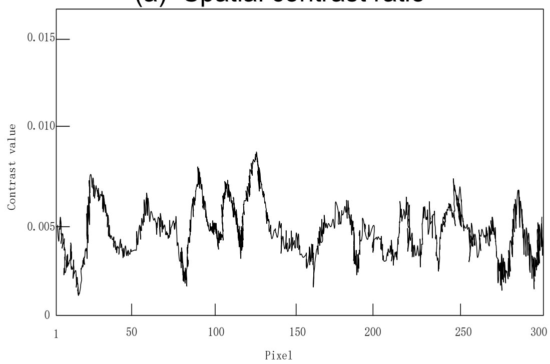


(a) Spatial contrast ratio

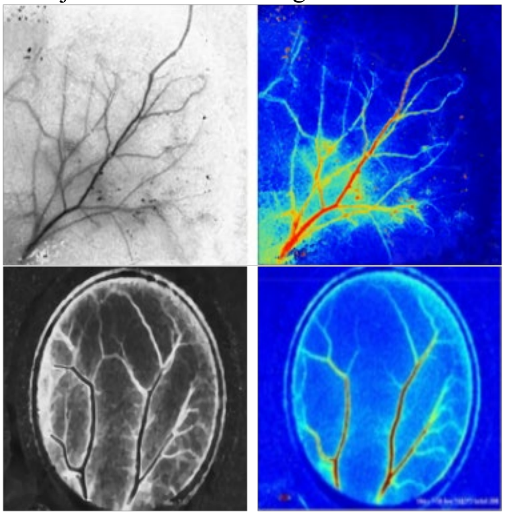


(b) Time contrast ratio

Figure 3. Spatial and temporal contrast results

According to Figure 3, it can be seen that the spatial contrast value fluctuates greatly in the presence of static scattering, and the contrast value curve shows significant fluctuations multiple times. Among them, when the pixel is around 115, the fluctuation of the contrast value reaches 0.015. However, the overall time contrast value curve shows small fluctuations, with the maximum contrast value only being 0.0041. Compared to the time spatial contrast value, it can be seen that the value of the time contrast value curve is lower, the fluctuation amplitude is smaller, and the stability is higher. This indicates that static scattering has a greater impact on spatial contrast analysis, while temporal contrast analysis has a smaller impact. Therefore, when using speckle contrast to study the motion of scattered particles, it is necessary to fully consider the influence of static scattering on spatial speckle contrast to ensure the reliability of imaging results.

Under the laser speckle imaging technology, the imaging image of deep blood flow distribution in sports injuries and the feature segmented target area map were analyzed. Therefore, the imaging and segmentation effects of the two methods for blood flow distribution in sports injuries are shown in Figure 4.



(a) Original image (b) Laser speckle imaging

Figure 4. Imaging of blood flow in sports injuries

The left side in Figure 4 shows the collected original image, and the right side shows the effect of laser speckle imaging. According to Figure 3, it can be seen that the deep blood flow distribution characteristic image of sports injury is imaged by the method proposed in this paper, and its distribution is presented in color, making the blood flow distribution image clearer and the contour more obvious. Smaller capillaries can be observed directly. Therefore, it can be seen that under the interference of reflection static speckle caused by swelling, the blood flow distribution characteristic image of sports injury in this paper's method is more effective, which effectively improves the quality of speckle imaging and provides support for observing the deep blood flow distribution characteristics of sports injury under laser speckle imaging.

To verify the effectiveness of the improved method, non rigid registration method, evolutionary gravity neurotron neural network method, and image registration method were compared with the improved method in the experiment, and the DICE coefficient was used as the indicator for experimental verification. The results are shown in Figure 5:

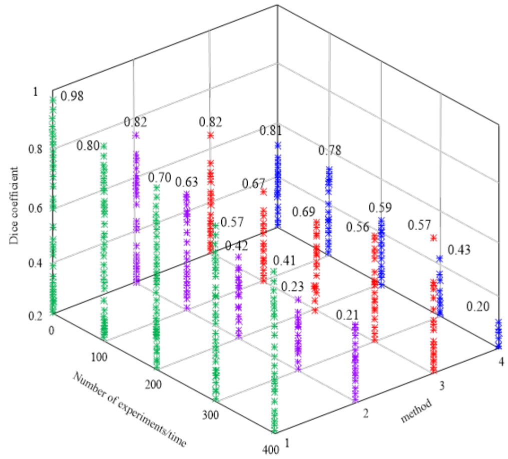


Figure 5. Comparison results of DICE coefficients

In Figure 5, Method 1 is an improved method, Method 2 is a non rigid registration method, Method 3 is an evolutionary gravity neurotron neural network method, and Method 4 is an image registration method. As shown in Figure 5, when using non rigid registration methods, as the number of experiments increases, although its DICE coefficient is relatively stable, the overall DICE coefficient value is low, with an average DICE coefficient of about 0.61; When using the evolutionary gravity neurotron neural network method, as the number of experiments increases, the DICE coefficient shows a fluctuation phenomenon of first increasing, then decreasing and then increasing, with an average DICE coefficient of 0.58; When using image registration methods, as the number of experiments increases, the DICE coefficient shows a decreasing trend, indicating that the image registration method is greatly affected by the number of experiments and is not suitable for large-scale use; When using the improved method, the DICE coefficient shows a decreasing trend with the increase of experimental times, but the decreasing trend is small and can be ignored. The average DICE coefficient is 0.93, which is improved compared to non rigid registration methods, evolutionary gravity neural network methods, and image registration methods. This is because using ultrasound light scattering imaging can intuitively display the severity of damage, making the imaging effect better and having certain advantages.

To verify the effectiveness of the improved method, non rigid registration method, evolutionary gravity neurotron neural network method, image registration method and the improved method were compared in the experiment, and MPA value and GPI_j value were used as indicators for experimental verification. The results are shown in Figure 6:

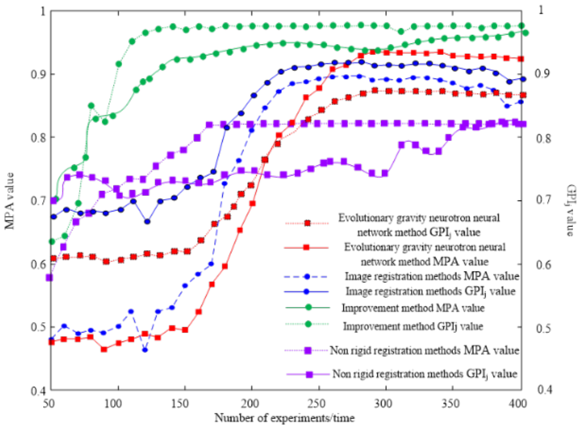


Figure 6. Comparison Results of MPA and GPI_j

As shown in Figure 6, when using the non-rigid registration method, as the number of experiments increases, although its MPA value gradually increases and tends to stabilize, the average MPA value is about 0.78.

When using the EGNNN, as the number of experiments increases, the growth trend of MPA value is slow. Although there is a stable and upward trend in the later stage, the average MPA value is 0.68; When using image registration methods, as the number of experiments increases, the MPA value shows multiple fluctuations such as a decrease and an increase, indicating that the image registration method is greatly affected by the number of experiments and is not suitable for large-scale use.

When using the improved method, its MPA value showed a gradually increasing trend with the increase of experimental times. Although there was a small fluctuation in the early stage, it had a small impact on its overall MPA value, and the average MPA value was 0.96.

Compared with non rigid registration, EGNNN, and image registration, it was improved because using ultrasound light scattering imaging can intuitively display the severity of damage, making the imaging effect closer to the real situation and having certain advantages.

When using non rigid registration methods, as the number of experiments increases, although the GPI_j value gradually increases, the overall fluctuation is large and there are sudden decreases and increases in multiple places, with an average GPI_j value of about 0.76; When using the EGNNN, with the increase of experimental times, there is an upward trend in the later stage, but the average GPI_j value is 0.73.

When using image registration methods, as the number of experiments increases, there are fluctuations such as a decrease or an increase in values, with an average GPI_j value of 0.84.

When using the improved method, the GPI_j value gradually increased with the increase of experimental times. Although there was a small fluctuation in the early stage, it had a small impact on the overall GPI_j value, and the average GPI_j value was 0.97.

Compared with non rigid registration, EGNNN, and image registration, the GPI_j value improved. This is because using ultrasound light scattering imaging can intuitively display the severity of damage, making the imaging effect better and having certain advantages.

In order to further verify the imaging efficiency of the proposed method, the non-rigid registration, EGNNN, image registration are compared with the proposed method according to the imaging time T. The mean value of imaging time is taken for statistics, and shown in following Table 3.

Table 3. Time of Imaging

Test Times	Time/s			
	The proposed method	Non-rigid registration	EGNNN	image registration
50	3.114	7.341	6.427	5.587
100	3.135	7.332	6.415	5.579
150	3.103	7.346	6.438	5.564
200	3.117	7.337	6.426	5.573
250	3.124	7.352	6.421	5.581
300	3.105	7.343	6.431	5.572
350	3.112	7.347	6.417	5.569
400	3.125	7.336	6.428	5.570

According to Table 3, when the non-rigid registration method is adopted, the imaging time is the highest among the four methods, and the shortest imaging time is 7.332s. When the EGNNN is used, the imaging time is lower than that of the non-rigid registration, and the shortest imaging time is 6.415s. When the image registration is used, the imaging time is the shortest among the three comparison methods, and the shortest imaging time is 5.564s. When the proposed method is adopted, the imaging time is the shortest among the four methods, the shortest is 3.103s, and the longest is only 3.135s.

Therefore, comparing the results of the above four methods, it can be concluded that the improved method can effectively shorten the imaging time and improve the efficiency and practicability of the imaging method of deep blood flow distribution. This is because the proposed method introduces exponential Laplace loss function with stochastic gradient descent, effectively reduces the distance of blood flow features within same class of sports injuries, reduces the amount of computation, and enables rapid identification and separation of blood flow features related to sports injuries. It reduces the time of feature extraction and analysis, and ensures the effective use of data. Thus, the efficiency of imaging is improved.

6. Conclusion

With the continuous development of computer and communication technology, laser speckle imaging technology has been widely applied. The current laser speckle imaging method for deep blood flow distribution characteristics of sports injuries cannot meet the requirements of resisting static speckle interference. Therefore, it is necessary to construct an imaging method with better imaging effect. According to the recognition requirements, an exponential Laplace loss function is introduced to reduce the amplitude of changes in blood flow characteristics of intra class sports injuries and collect deep blood flow distribution characteristics of sports injuries; On the basis of calculating the laser speckle contrast ratio, the blood volume flow rate is determined, and the blood volume flow rate data is combined with the laser speckle contrast ratio to achieve imaging of deep blood flow distribution in sports injuries. Through experimental testing of imaging effect, DICE coefficient, average accuracy MPA, and global imaging index GPI_j, it was found that:

(1) The improved laser speckle imaging technology has a better imaging effect in the imaging of deep blood flow distribution in sports injuries;

(2) The downward trend of the DICE coefficient of the improved laser speckle imaging technology with the increase of experimental times is negligible, and the average DICE coefficient is 0.93;

(3) The average accuracy MPA value of the improved laser speckle imaging technology gradually increases with the increase of experimental times, and the average MPA value can reach 0.96;

(4) The global imaging index of the improved laser speckle imaging technology shows the same trend as the average accuracy MPA value with the number of experiments, and the average global imaging index value can reach 0.97.

The experimental results show that the improved laser speckle imaging technology can effectively achieve imaging of deep blood flow distribution in sports injuries, and the imaging effect is closer to the real situation, which has certain advantages and reliable application value. In future, cognition will be considered to guide the imaging processing [22].

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