Laboratory Abnormal Behavior Recognition Method Based on Skeletal Features

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***Abstract*—The identification of abnormal laboratory behavior is of great significance for the safety monitoring and management of laboratories. Traditional identification methods usually rely on cameras and other equipment, which are costly and prone to privacy leakage. In the process of human body recognition, they are easily affected by various factors such as complex backgrounds, human clothing, and light intensity, resulting in low recognition rates and poor recognition results. This article investigates a laboratory abnormal behavior recognition method based on skeletal features. One is to use Kinect sensors instead of traditional image sensors to obtain characteristic skeletal data of the human body, reducing external limitations such as lighting and increasing effective data collection. Then, the collected data is smoothed, aligned, and image enhanced using moving average filtering, Discrete Fourier Transform, and contrast, effectively improving data quality and helping to better identify abnormal behavior. Finally, the OpenPose algorithm is used to construct a laboratory anomaly behavior recognition model. OpenPose can be used to connect the entire skeleton through the relationships between points during the process of extracting human skeletal points, and combined with multi-scale pyramid networks to improve the network structure, effectively improving the accuracy and recognition speed of laboratory abnormal behavior recognition. The experiment shows that the accuracy, precision, and recall of the behavior recognition model constructed by the algorithm are 95.33%, 96.68%, and 93.77%, respectively. Compared with traditional anomaly detection methods, it has higher accuracy and robustness, lower parameter count, and higher operational efficiency.**

Keywords*—*Skeletal features; abnormal behavior recognition; OpenPose algorithm; Kinect sensor; Discrete Fourier Transform

I. Introduction

In recent years, the rapid development of computer vision and artificial intelligence technology has brought major changes to many industries. Among them, motion recognition technology, as a key branch, is gradually being integrated into all aspects of people's lives. In the scientific research laboratory environment, efficient and accurate identification of abnormal behaviors is essential to ensure the safety of personnel, the normal operation of equipment, and the reliability of experimental results. However, the traditional recognition method based on video surveillance has shortcomings in dealing with lighting changes, line of sight blocking and viewing angle restrictions, which affects the accuracy and stability of recognition. To meet these challenges, this study proposes a strategy for identifying abnormal behaviors based on human skeletal Features. By using the OpenPose algorithm and the Kinect depth sensor, it is possible to accurately capture and extract the three-dimensional bone structure data of the experimenter. As the internal manifestation of human movement, bone characteristics can not only effectively reflect the relative position and trajectory of joints, but also have a higher tolerance and anti-interference ability to light, color changes and background complexity, and show excellent robustness in complex laboratory environments.

By constructing a laboratory abnormal behavior recognition model based on skeletal Features, it aims to break through the limitations of traditional video surveillance technology, realize in-depth analysis of the movements and attitudes of experimenters, and detect and warn of potential safety hazards or operational errors in a timely manner. This research is expected to significantly improve the level of safety management in the laboratory, and provide strong support for the optimization and efficiency improvement of the experimental process. Therefore, the introduction of skeletal features into the field of abnormal behavior recognition in laboratories is not only an inevitable trend of technological development, but also a practical need to ensure the smooth progress of scientific research activities and promote the sustainable prosperity of scientific undertakings.

II. Related Work

Abnormal behavior recognition is the process by which a monitoring system compares and identifies behaviors or events that do not conform to known conventional behavior patterns [1-2]. This method can analyze the patterns existing in the data, identify some behaviors that do not conform to the norm, and timely discover and respond to potential problems or dangers. Li Lin developed an abnormal behavior recognition method based on the spatiotemporal background of learning behavior. The specific recognition method adopts a top-down strategy and evaluates the effectiveness of local behavior themes and abnormal behavior recognition using spatiotemporal context learning [3]. Guan Yepeng proposed an abnormal behavior recognition method based on three-dimensional convolutional neural network (CNN) and long short-term memory (LSTM), which replaces the three primary color images with a feature image composed of optical flow and motion history images as input [4]. Hao Yixue combined Graph Convolutional Network (GCN) and 3D Convolutional Neural Network to propose an end-to-end anomaly behavior detection framework from a new perspective. Specifically, a class of classifiers is trained to extract features and estimate anomaly scores to improve the performance of anomaly behavior detection [5]. Shi Xiaonan proposed an underground abnormal behavior recognition method based on optimized Alphapose-GCN. Firstly, he defogged and enhanced the image set captured in the underground monitoring video. Secondly, he optimized Alphapose object detection using the YOLOv3 model. Finally, he performed abnormal behavior recognition [6]. Bae Hyun-Jae proposed a method to identify abnormal behavior using only joint keypoints and joint motion information. He extracted joint keypoints of body parts through AlphaPose and sequentially inputted the extracted joint keypoints into the LSTM model for recognition [7]. Lee Jiyoo proposed an anomaly behavior detection model based on deep learning models, which reflects the accuracy of this research method for anomaly behavior detection by detecting violent and fainting behaviors in videos [8]. In summary, although the existing methods can cope with the challenges of lighting, occlusion, and viewing angle changes, the recognition accuracy rate may decrease in extremely complex scenes, and enhancing the robustness of the algorithm in complex environments is an urgent problem to be solved. At the same time, the definition of abnormal behavior in different scenes and contexts is different, and there are ambiguities and ambiguities. Building a common and highly explanatory abnormal behavior recognition framework to adapt to different application scenarios is another important issue. To this end, this article will use the bone feature research method to study it, hoping to improve the accuracy of recognition.

Behavior recognition based on bone features is a combination of machine vision and deep learning, which can analyze and recognize human motion and behavior [9-10]. This method monitors and analyzes human movement by detecting key parts in the human skeleton. TIAN Zhiqiang designed a temporal divergence model based on skeleton points to describe the motion state of skeleton points, amplifying the inter class differences in different human behaviors. At the same time, he also designed an attention mechanism with temporal divergence features to highlight key skeleton points, and this algorithm has a relatively high accuracy in authoritative human behavior datasets [11]. Liu Yuchao extracted key points of the human 3D skeleton in time series using YOLOv4, and applied the Meanshift object tracking algorithm to convert the key points into spatial tricolors. He put it into a multi-layer convolutional neural network for recognition, which can quickly identify various abnormal behaviors [12]. Li Maosen used two chart scales to clearly capture the relationship between body joints and body parts, and conducted experiments on skeleton-based motion recognition and prediction on four datasets, achieving good results [13]. Gao Guohong introduced an extraction technique that combines jawbone skeleton features, using skeleton heatmap descriptors and Kalman filtering algorithm to extract skeleton features of the upper and lower jaw bones. This method has better recognition accuracy than other models [14]. Shu Xiangbo proposed a new skeleton joint method to capture spatial consistency between joints and temporal evolution between skeletons. At the same time, he found through experiments on human motion prediction that the proposed method is superior to other methods on the feature maps that are of common concern to the skeleton joints [15]. Through the integration of machine vision and deep learning, the behavior recognition method based on bone characteristics has significantly improved the accuracy of human movement and behavior analysis. The current research mainly focuses on the precise detection of key bone points and the establishment of motion state models. Technical methods such as time divergence model, attention mechanism, and tracking of key points of the three-dimensional skeleton are used to further highlight the differences between different behaviors, thereby improving the accuracy of recognition. These studies have not only enhanced bone feature recognition technology, but also provided solid support for practical application scenarios such as laboratory abnormal behavior monitoring.

Today, with the increasing awareness of laboratory safety, it is crucial to effectively detect and prevent abnormal laboratory behavior. Although traditional video monitoring technology can monitor the situation inside the laboratory in real time, it often requires manual monitoring and analysis, which is not only inefficient but also prone to missed detections. The abnormal behavior recognition method based on bone features automatically identifies abnormal behaviors by capturing and analyzing bone movements, to improve the efficiency of laboratory safety management. This project aims to identify abnormal behaviors in the laboratory based on bone characteristics.

III. Bone Feature Extraction Technology

This article uses bone feature extraction technology to extract bone points from abnormal behaviors in the laboratory. Firstly, the video data in the laboratory is captured by a camera, and more features are extracted from human bones using Kinect depth sensors. By analyzing the collected bone structure data, important evidence can be provided for subsequent identification of abnormal behavior [16-17]. Skeleton points are a type of landmark data. The human skeleton is the internal framework of the human body, which generally includes two elements: joints and bones. Bones are the lines connecting points and edges, and joints and bone elements correspond exactly to edges and points in the shape [18]. Therefore, the skeleton structure is shown in Fig. 1.

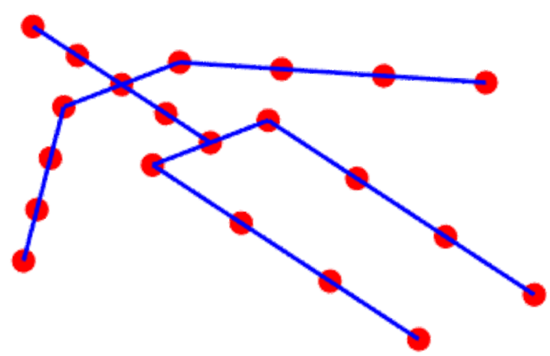

Fig. 1. Skeleton diagram.

There are two main methods for obtaining human skeletal information: one is posture estimation [19], and the other is motion capture devices [20-21]. The human skeletal sequence is based on the two-dimensional or three-dimensional coordinates of human joints. On this basis, the coordinate vectors of each node can be correlated and an independent feature vector can be generated between each frame. This article utilizes Kinect depth sensors for bone feature extraction.

Kinect depth sensors first obtain a continuous stream of human body sequence data based on the actions of the experimenters. Through this stream of sequence data, corresponding depth images can be obtained. By preprocessing the obtained images, the coordinates of the actions in three-dimensional space and time series can be obtained. By collecting joint point data through Kinect, the first step is to segment the collected human body contours. During this process, Kinect filters and distinguishes each pixel point to find the pixel that is most likely to be the human body boundary. Then, edge detection algorithms are used to identify the contour area of the target. On this basis, the extracted human body contours were used to segment the torso and limbs of the human body.

When performing behavior recognition, only representative skeletal parts such as hands and feet are usually needed to make corresponding recognition and judgment of actions. These skeletal points all have one thing in common, which is that they are far from the center of gravity of the body, have a larger range of motion and higher flexibility. Compared to the more fragile skeletal parts of the human body, the wrist and ankle joints play a more important role in human behavior recognition. Taking the center of gravity of the human body as a reference, the line h connecting the center of gravity to other bone points represents the relative distance between each bone point and the center of gravity of the human body. Therefore, at adjacent moments $[t + \Delta t]$, the average distance H from bone point j_i to the center of gravity can be expressed as:

$$\bar{h}_i^t = \left(|h_i^t| + |h_i^{t+\Delta t}|\right)/2 \tag{1}$$

Among them, the $\bar{h} \in [0,1]$ and $\bar{h}$ values are too small to serve as characterizations. Here, β is used to activate the function and normalize h¯to a new interval [x, y]. The specific expression is as follows:

$$\beta(a) = ln(a + q) + p \tag{2}$$

Let $a = H$ analyze the original interval [0,1] and the generated inter new area $[x, y]$ to solve.

$q = 1/(e^{y-x} - 1)$ and $p = y - ln\left(\left(e^{y-x}/\left((e^{y-x} - 1)\right)\right)\right)$.

Human abnormal behavior is very random and difficult to predict. It is impossible to describe the entire abnormal behavior of the human body well if only one feature is extracted. So, this article uses two skeletal features, namely the aspect ratio of the human body and the structural vector, to study, and the expression for the aspect ratio of the human body is as follows:

$$x = \frac{a}{b} \tag{3}$$

Among them, x represents the aspect ratio of the human body, a represents the width of the smallest outer rectangle, and b represents the height of the smallest outer rectangle.

IV. Data Collection and Preprocessing

A. Data Collection

With the rapid development of the chemical industry, the number of chemical laboratories is gradually increasing, and their safety issues are also increasingly attracting social attention. To ensure safety during the experiment, it is necessary to detect and identify potential abnormal behaviors of the experimental personnel. A unique chemical laboratory dataset was established by collecting and cleaning chemical experimental data from public datasets. To improve the efficiency and accuracy of data classification and labeling, YOlOv5 is introduced in the process of establishing the behavior model to complete relevant behavior classification and labeling, thereby enhancing the overall recognition performance of the model. The tag files used in this article are in the format of the dataset and are marked using current open and convenient tagging tools. In behavior recognition experiments based on human bones, the NTU RGB+D dataset has the largest number of samples so far, including multiple video sequences. This article collects a total of 60 different action categories. This dataset was collected by Kinect sensors and synchronously observed from multiple perspectives. The collected data is shown in Fig. 2.

Fig. 2. Partial dataset collection.

B. Data Preprocessing

1) Data smoothing processing: Due to the performance of Kinect sensors themselves, there may be some additional noise in the collected data. In addition, when experimental participants engage in behavioral movements, noise may also be present in the data due to factors such as body tremors. To eliminate noise in the data, it is necessary to perform smoothing processing, i.e. filtering, on the data. For this purpose, this article uses the moving average filtering method [22-23] to process the collected data. This method averages a fixed length signal to achieve the goal of eliminating noise. Take the data segment $A_1, A_2, \cdots, A_H$ with a fixed length of H, and the specific calculation formula is as follows:

$$\bar{A} = \frac{1}{H}\sum_{i=0}^{H} A_{H-1} \tag{4}$$

Among them, $\bar{A}$ is the average value of H data points, which can be used to replace the current position of A_1 data points. Then, starting from A_2, H data points are taken, and the average value is calculated to replace A_2. After n iterations of the above process, n filtering smoothing results are obtained.

The data smoothing effect based on the moving average method is shown in Fig. 3. It can be found that using moving average to smooth the data has achieved very good results, and the data can retain more original features.

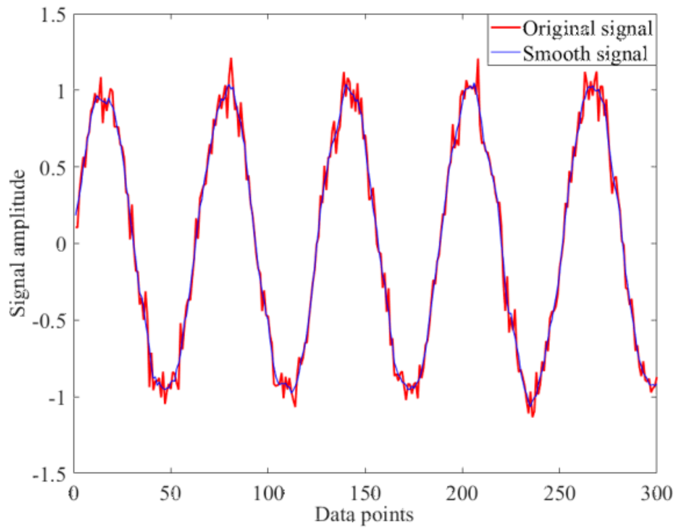

Fig. 3. Data smoothing effect based on moving average method.

2) Data alignment processing: The process of obtaining human bone data based on Kinect sensors is real-time, and different action intervals result in different lengths of each set of data even at the same sampling frequency [24-25]. In addition, the influence of factors such as the technical level and operating habits of the experimenters results in different completion times for the same action participants, leading to different data lengths. Therefore, it is necessary to align the collected bone data to achieve effective learning and prediction of human behavior. Discrete Fourier Transform is the process of converting n signals that were originally in the time domain to obtain an equal number of signals in the frequency domain [26-27]. Assuming that a non-periodic continuous time signal is denoted as y(t), the Fourier transform expression for this signal is as follows:

$$Y(\beta) = \int_{-\infty}^{+\infty} y(t)e^{-jet}dt \quad (5)$$

This article adopts the data alignment method of Fourier transform, and the specific effect diagram is shown in Fig. 4.

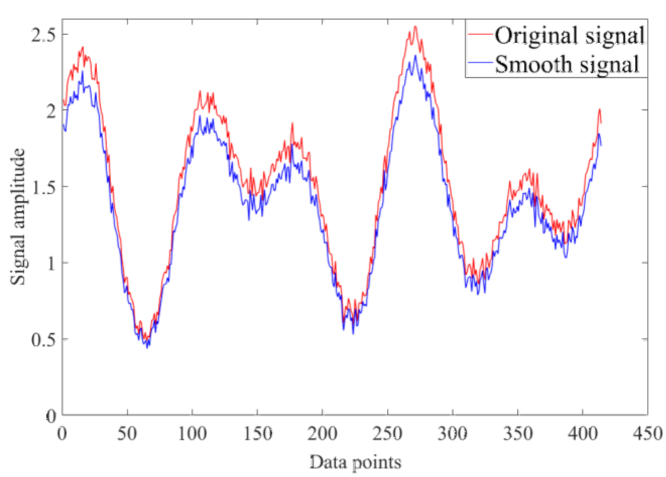

Fig. 4. Data alignment effect based on fourier transform.

As shown in Fig. 4, the length of the bone action data signal is 414, and the target length is 450. By interpolation, human behavior data of the same length can be obtained. Therefore, this also indicates that using Fourier transform can obtain human behavior feature data of the same length, achieving the purpose of data alignment.

3) Contrast enhancement: Image contrast refers to the difference in brightness of an image, while contrast enhancement refers to the difference in grayscale colors in an image, making the content of the image clearer [28-29]. The expression for contrast enhancement is as follows:

$$h|(a) = xg(a) + y \quad (6)$$

Among them, g(a) represents the input data; g(x) is the output data; x is the gain, which can set the contrast of the image; y is paranoia, which can set the brightness of the image.

If it is necessary to enhance the contrast of non-linear images, x and y methods are usually automatically selected. Assuming the height of the input matrix Q is H and the width is W, $Q(s,t)$ represents the grayscale value of the s row and t column. The minimum grayscale value in matrix Q is Q_{min}, and the maximum value is Q_{max}, which means the grayscale value of the matrix is $Q_{min} \leq Q(s,t) \leq Q_{max}$. The range of the output matrix R is $[R_{max}, R_{min}]$, and the expression is as follows:

$$R(s,t) = \frac{R_{max}-R_{min}}{Q_{max}-Q_{min}}(Q(s,t) - Q_{min}) + R_{min} \quad (7)$$

Among them, $0 \leq s \leq H$, $0 \leq t \leq W$, and $R(s,t)$ represent the grayscale values of the s row and t column. Generally, $R_{min} = 0$ and $R_{max} = 255$ are set.

The effect of using contrast enhancement to enhance the collected laboratory behavior images is shown in Fig. 5.

a b

Fig. 5. Effect image based on contrast enhancement.

As shown in Fig. 5, 'a' is the original image, and 'b' is the image after contrast enhancement. The use of contrast enhancement methods can effectively enhance the clarity of images, making their brightness more pronounced and highlighting key information.

V. Construction of a Laboratory Abnormal Behavior Recognition Model Based on OpenPose

Compared with 2D images, bone sequences can more accurately reflect the spatial distribution positions of various joints in the human body, but cannot effectively characterize the connection status between joints in the human body. To better express the semantics of complex interaction behaviors, this article can use graph data structures to characterize the connection states between joints, and based on this, study a behavior feature description method based on time-space graphs. On the one hand, spatial graph connections can be designed based on the characteristics of individual bones in the frame and the corresponding joint interactions between two individuals; On the other hand, connectivity methods for temporal graphs can be studied based on the mapping relationships between nodes in each frame. Through these operations, the connectivity status of each bone node in the spatial region can be achieved, achieving spatiotemporal description of interaction behavior. The OpenPose algorithm is a bottom-up approach for behavior recognition. This algorithm can recognize human body movements, facial expressions, etc., and has good noise resistance [30-31]. The backbone extraction network of OpenPose adopts a variant based on ResNet, mainly composed of deep residual neural networks. This network can accept input from images of any size and convert the input images into feature maps of the same size. In the transformed feature map, multi-layer convolution and pooling layers are used to extract features from the image. At the final layer of the network, the obtained feature map is transformed into a local thermal spectrum for extracting bones, thereby achieving localization of various parts of the human body. This method maps the temperature distribution of various parts of the human body to obtain the temperature distribution of each part of the human body, thereby completing the pose estimation of the human body.

When using preprocessed data with OpenPose to identify abnormal behavior, although the novelty of this method may be affected by the wide application of OpenPose, it does not prevent innovation in data processing and model construction. As a key link to ensure the performance of the model, data preprocessing explores a more efficient bone feature extraction technology for the data generated by OpenPose, and tries to incorporate novel features to enhance the expressive force of the data. The construction of recognition model is the core of this study. Based on the skeleton information extracted by OpenPose, a variety of machine learning and deep learning models are skillfully designed and trained to achieve a breakthrough in the field of abnormal behavior recognition. These measures not only highlight the innovation of research, but also are expected to significantly improve the accuracy of abnormal behavior identification.

OpenPose has excellent ability to identify and locate key points of human body, and can capture multiple key points of face, hands, feet and main parts of the body at the same time, with a total of 25 points. This comprehensive detection enables the algorithm to grasp the human posture more accurately, and then accurately judge the abnormal behavior in the laboratory. At the same time, the algorithm uses the human body component decoder to determine the relationship between key points, which helps the algorithm to understand the human posture structure more deeply, thus improving the recognition accuracy. This design makes the algorithm perform better in dealing with complex human movements and posture changes, and effectively reduces misjudgment. In addition, OpenPose also uses multi-scale pyramid network to detect the human contour and key points, and then improves the positioning accuracy through gradual thinning. This structure is efficient and accurate. In practical application, lightweight OpenPose models can be selected to reduce the computational load and improve the recognition speed. These models significantly reduce the demand for computational resources while maintaining high accuracy. In addition, OpenPose also adopts efficient strategies such as parallel processing and cache optimization to further reduce the amount of computation and time consumption, and ensure that the algorithm can quickly process the input and output the recognition results.

In this article, human behavior and actions are recognized based on human bone data, mainly through the acquisition of human bone information through Kinect sensors. The obtained bone information is used as the three-dimensional coordinate values of various joint nodes in the human body. After completing a behavior, the experimental participants can obtain the corresponding bone data stream and save this bone data with a dimension of 48 * L, where L refers to the length taken during the data alignment process. OpenPose can be used to connect the entire skeleton through the relationship between points during the extraction process of human skeletal points [32-33]. The coordinate vectors of S joint points can be used to express the initial input bone data within one frame. For any t-the frame, the initial input data can be represented as $A_t \in Q^{Z_0 * S}$, Z_0 represents the coordinate dimension of the input original bone data, and t represents the t-th frame bone data. To better capture the relationship between the corresponding joint connections and behavioral semantics between adjacent frames, a frame-to-frame time graph connection design is performed for each frame of joint data, combined with the joint data of the previous and subsequent frames. The expression is:

$$m_{a,b} = \begin{cases} \alpha & (a,b) \in \aleph_5 \\ \beta & (a,b) \in \aleph_6 \\ 0 & a = b \end{cases} \tag{8}$$

Among them, $m_{a,b}$ describes the different weights α and β given to the edge response calculation when the joint point a and the joint point b belong to different connection categories ℵ_5 and ℵ_6 in the connection diagram.

Therefore, the adjacency matrix of the inter-frame time graph can be expressed as:

$$W_{t,t+1} = \begin{bmatrix} E_1 & E_2 \\ Q_1 & Q_2 \end{bmatrix} \tag{9}$$

Among them, E_1 and E_2 describe the joint relationship between the interaction parties between frames and themselves, as well as the joint connection relationship between Q_1 and Q_2 interaction parties and the interaction object between frames, jointly constructing a time graph description of interaction behavior between frames.

When human behavior is different, there can be a certain angle relationship between limbs due to deformation, and the angle information has good scale invariance. In addition, in laboratory settings, abnormal behavior exhibits strong mobility in many aspects compared to normal behaviors such as standing or standing on the left. Therefore, using joint angles as separate data to analyze abnormal behavior is very useful. The formula for calculating the joint angle is as follows:

$$\theta_{n,m} = arccos\frac{\gamma\cdot\delta}{|\gamma||\delta|}, |\gamma| \neq 0, |\delta| \neq 0 \tag{10}$$

Among them, $\theta_{n,m}$ represents the angle value of the nth joint in frame m, m is the inner product of the vector, || is the modulus of the vector, γ and δ represent the limb vectors corresponding to the joint angle, respectively.

The appearance characteristics of the human body reflect the proportion of the body shape during movement, which is a highly recognizable information. In laboratory settings, abnormal human behavior exhibits more significant movement characteristics than normal behavior, that is, during the movement process, abnormal behavior can undergo corresponding changes in its appearance due to the significant movement of limbs. The expression for calculating the proportion of human body shape is as follows:

$$ratio_i^k = \frac{max(l_1^k,\cdots,l_m^k)-min(l_1^k,\cdots,l_m^k)}{max(d_1^k,\cdots,l_m^k)-min(d_1^k,\cdots,d_m^k)} \tag{11}$$

Among them, i represents the current frame rate, k represents the kth person in the current frame, $(d_1^k,\cdots,d_m^k)$ and $(l_1^k,\cdots,l_m^k)$ represent the d and l coordinates of the kth human joint point, respectively.

This article can input preprocessed data into the OpenPose model. Firstly, the image features can be extracted through the backbone extraction network. Then, the key points in the image can be associated with each other to extract the confidence interval of the bone points. The optimal algorithm can be used to locate the key points, resulting in a bone structure map. The identification results of key areas for abnormal behavior (sleep) of experimental personnel are shown in Fig. 6.

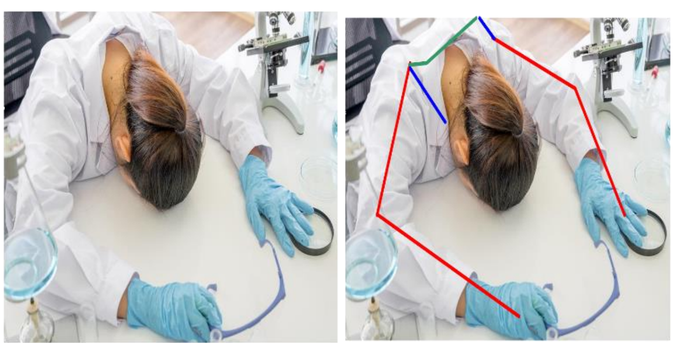

Fig. 6. Comparison of abnormal behavior before and after processing.

As shown in Fig. 6, the OpenPose model can effectively identify abnormal behaviors of experimenters. When abnormal behaviors occur during sleep, the OpenPose model can quickly capture and process corresponding bone information. On this basis, the OpenPose model utilizes convolutional neural networks to extract bone features and inputs them into a recurrent neural network to model the sequence. Therefore, it can effectively obtain time series information of human posture and improve the estimation accuracy of moving targets.

VI. EXPERIMENT OF LABORATORY ABNORMAL BEHAVIOR RECOGNITION MODEL BASED ON OPENPOSE ALGORITHM

A. *Experimental Preparation*

The specific environment configuration of the server is shown in Table I.

TABLE I. MODEL PARAMETER SETTINGS

Serial number	Experimental environment	Parameter
1	Central processing unit	Intel Xeon(R) E5-2620
2	Operating system	Ubuntul6.04 LTS
3	Deep learning framework	Pytorch 0.4.0
4	Programming language	Python 3.5
5	Initial learning rate	0.01
6	Weight attenuation coefficient	$1*10^{-4}$

Based on the characteristics and safety requirements of the laboratory itself, abnormal behavior can be classified according to specific regulations and laboratory safety needs. Meanwhile, corresponding discrimination criteria were established based on different types of abnormal behaviors. The specific abnormal targets that need to be detected for each type of experiment are shown in Table II.

TABLE II. REQUIREMENTS FOR DETECTING ABNORMAL TARGETS IN DIFFERENT EXPERIMENTS

Serial number	Abnormal behavior	Test set	Experiment set	Verification set	Total
1	Sleep	1040	130	130	1300
2	Long hair	640	80	80	800
3	Without gloves	720	90	90	900
4	Illegal disposal of waste	400	50	50	500
5	Eat	960	120	120	1200
6	Smoking	1120	140	140	1400
7	Play with mobile phone	1760	220	220	2200
8	Playing and running	2400	300	300	3000
Total		9040	1130	1130	11300

As shown in Table II, it can be observed that abnormal behavior is divided into eight categories, each of which is divided in a certain proportion into test set, experimental set, and validation set. Among them, the abnormal behavior of playing and running has the highest amount of data, while the abnormal behavior of illegal disposal of waste has the lowest amount of data.

B. Experimental Analysis

To achieve more accurate and scientific experimental results, multiple iterative experiments can be conducted. The 11,300 image data extracted in Table II are studied. In order to make the experimental results more accurate and scientific, multiple iterative experiments will be conducted, and the accuracy, accuracy, recall rate, and F1-Measure (F1 value) obtained from the laboratory abnormal behavior recognition model constructed based on the proposed method will be experimentally compared with the convolutional neural network (CNN) [4], Spatial-Temporal Context visual tracking (Spatio-Temporal Context, STC) [3], AlphaPose algorithm [6] , Long Short-Term Memory network (Long Short-Term Memory, LSTM) [7] , Graph Convolutional Network (GCN) [5] and Meanshift [12] abnormal behavior recognition model constructed by the algorithm is compared, and the specific model performance comparison results are shown in Table III.

TABLE III. PERFORMANCE COMPARISON OF DIFFERENT ABNORMAL BEHAVIOR RECOGNITION MODELS

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 value (%)
Proposed	95.33	96.68	93.77	94.38
CNN	87.41	88.12	84.14	85.31
STC	86.25	84.91	80.47	81.59
AlphaPose	80.94	81.48	77.75	75.09
LSTM	86.39	89.12	82.66	80.67
GCN	82.63	84.39	83.97	82.07
Meanshift	84.61	82.77	81.73	80.33

As shown in Table III, the performance of the laboratory abnormal behavior recognition model constructed by the proposed algorithm in this paper is better than that of other algorithms in all aspects, which shows that the method studied in this paper can better detect and identify abnormal behaviors that occur in the laboratory. Behavior. The accuracy rate of the behavior recognition model constructed based on the proposed method is 95.33%, which is higher than that of the abnormal behavior recognition model constructed based on CNN, STC, AlphaPose, LSTM, GCN, and Meanshift algorithms. 7.92%、9.08%、14.39%、8.94%、12.7% And 10.72%.The high accuracy rate of the proposed method not only reflects its strong feature extraction and classification capabilities, but also its effectiveness in dealing with diverse abnormal behaviors in a laboratory environment. Compared with traditional visual methods such as CNN and STC, the proposed method can more accurately capture subtle changes in key points of human bones, so as to accurately distinguish between normal behavior and abnormal behavior. The accuracy rate of the method studied in this paper is 96.68%, which is 8% higher than the accuracy rate of the model constructed based on CNN, STC, AlphaPose, LSTM, GCN and Meanshift algorithms, respectively..56%、11.77%、15.2%、7.56%、12.29% and 13.91%, which means that the model has a lower false positive rate when identifying abnormal behavior, that is, it is less likely to misjudge normal behavior as abnormal.

At the same time, the recall rate of up to 93.77% ensures that the model can detect most real abnormal behaviors, significantly reducing the risk of missed inspections. This dual guarantee makes the proposed method of great practical value in laboratory safety control. The F1 value, as the reconciled average of the accuracy rate and recall rate, can more comprehensively show the overall performance of the model. The F1 value of the proposed method as high as 94.38% shows that it has done an excellent job in balancing accuracy and recall, once again confirming its superiority as a laboratory abnormal behavior recognition tool. The proposed algorithm can extract key point data of human bones from videos or images in real time and accurately, providing a valuable source of information for analyzing human posture and movement patterns. Although the comparison algorithms such as LSTM and GCN in Table III also incorporate time and graph structure information, the method relies on its unique attitude evaluation architecture to more naturally combine space-time background information, so as to more effectively capture the dynamic evolution of behavior evolution.

Research can be conducted on the extracted abnormal behavior data in Table II. Skeleton point extraction can be performed on the extracted abnormal behavior data images. The faster the extraction speed, the better for subsequent behavior recognition. This article can use the OpenPose algorithm to extract bone points from the collected images. The required extraction time can be compared with models constructed based on CNN, STC, AlphaPose, LSTM, GCN, and Meanshift algorithms. The specific comparison results are shown in Table IV.

TABLE IV. COMPARISON OF BONE POINT EXTRACTION SPEEDS AMONG DIFFERENT MODELS

Algorithm	1	2	3	4	5	6	7	8	Average value
Proposed	1.95	1.84	2.16	2.49	1.74	1.91	2.31	3.08	2.19
CNN	6.87	6.17	5.86	4.69	7.08	5.47	6.22	7.96	6.29
STC	3.34	2.96	2.88	4.02	4.81	4.39	5.93	5.22	4.19
AlphaPose	4.91	3.34	3.17	4.49	4.02	5.17	4.61	5.06	4.35
LSTM	5.64	4.06	5.49	6.07	4.86	6.02	4.77	5.83	5.34
GCN	5.13	4.46	4.97	6.39	4.08	3.84	5.06	6.28	5.03
Meanshift	3.58	3.27	4.51	3.28	5.18	4.63	5.88	6.31	4.58

As shown in Table IV, the comparative experimental results of different algorithms on the extraction speed of bone points are shown. First of all, the proposed method showed a significant speed advantage when extracting bone points of abnormal behavior images in Table II. The average extraction time is only 2.19 seconds, which is 4.1 seconds, 2 seconds, 2.16 seconds, 3.15 seconds, 2.84 seconds and 2.39 seconds lower than the time required for models built based on CNN, STC, AlphaPose, LSTM, GCN, and Meanshift algorithms, respectively. The time required for the model is 4.1 seconds, 2 seconds, 2.16 seconds, 3.15 seconds, 2.84 seconds, and 2.39 seconds. This advantage is not only reflected in the average time, but also in the stability and efficiency of the proposed method when dealing with various types of abnormal behaviors. Further analysis found that although the number of slapsticks running images numbered 8 is large, the proposed method can still complete bone point extraction within 3.08 seconds, compared to other algorithms such as CNN's 7.96 seconds, LSTM's 5.83 seconds, etc., its time advantage is particularly obvious. This proves the efficiency and robustness of the method in handling complex dynamic scenes. On the contrary, for the eating image numbered 5, although the number of images is large, the amplitude of its movement is relatively clear. The method can quickly capture these subtle changes and complete the bone point extraction at an extremely fast speed of 1.74 seconds, which further verifies the advantages of the algorithm in accurately capturing the posture of the human body. In addition, the proposed method can maintain a relatively stable time consumption when extracting bone points of different abnormal behavior images, without significant fluctuations, which shows that the algorithm has good generalization ability and stability, which is conducive to dealing with diverse scenarios and needs in practical applications. In summary, the proposed method with its excellent extraction speed and stability, provides strong support for the rapid and accurate identification of bone points in abnormal behavior images, and lays a solid foundation for subsequent behavior recognition work.

Eight possible abnormal behaviors that may occur in the laboratory were selected in Table II, and the eight selected abnormal behaviors were numbered 1-8. A laboratory abnormal behavior recognition model based on OpenPose algorithm can be used to detect these eight abnormal behaviors, and the accuracy of detecting each abnormal behavior can be obtained. The detected experimental results can be compared with the accuracy of models constructed based on CNN, STC, AlphaPose, LSTM, GCN, and Meanshift algorithms. The specific comparison results are shown in Fig. 7.

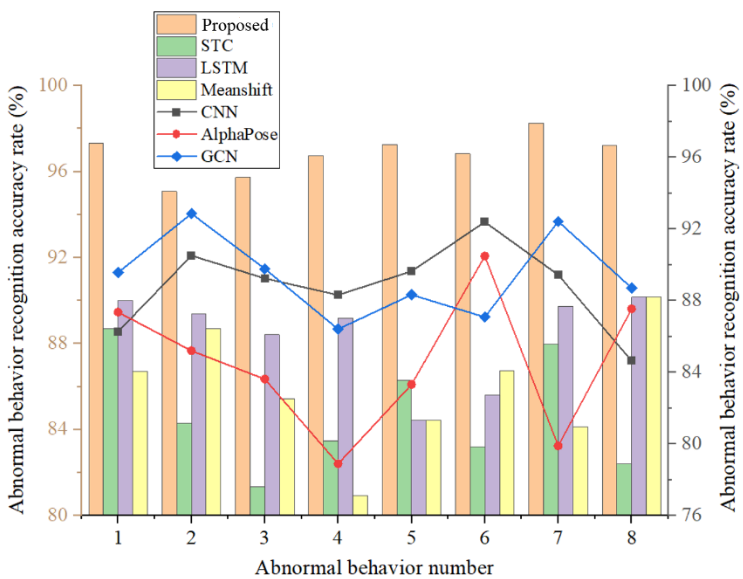

Fig. 7. Comparison of accuracy of different abnormal behavior recognition models for abnormal behavior recognition.

In Fig. 7, the x-axis represents the abnormal behavior number, and the left and right y-axis represent the abnormal behavior recognition accuracy. Among them, the recognition accuracy of the proposed method, STC, LSTM, and Meanshift algorithms refers to the left y-axis, while the CNN, AlphaPose, and GCN algorithms refer to the right y-axis. As shown in Fig. 7, the method has excellent performance in identifying these abnormal behaviors, and its average recognition accuracy rate is as high as 96.81%.Compared with other algorithms, the accuracy rate of the method is 8% higher than that of CNN, STC, AlphaPose, LSTM, GCN, and Meanshift, respectively..01%、12.1%、12.27%、8.44%、7.41% and 10.91%. Among them, the method's recognition rate exceeded 95.07% when dealing with all eight behaviors. Especially when it comes to identifying complex and subtle abnormal behaviors such as playing with mobile phones, its accuracy rate is as high as 98.27%, far surpassing other algorithms. Compared with other algorithms, the proposed method not only leads in the average accuracy rate, but also performs well in the recognition of each type of abnormal behavior. Compared with CNN and STC, the average accuracy rate of the method has improved significantly, showing high reliability and accuracy in dealing with diverse and complex abnormal behaviors in the laboratory. Compared with AlphaPose, which is also an attitude estimation algorithm, the method has more obvious advantages in identifying subtle movements and behaviors in complex scenes. Although the recognition rate of GCN in some cases is close to that of the method, overall, the proposed method still has an advantage in recognition accuracy and stability. In summary, this study experimentally verifies the excellent performance of the abnormal behavior recognition model based on the method in the laboratory environment. The model is not only efficient in bone point extraction, but also has a significant breakthrough in recognition accuracy, which provides strong support for behavioral monitoring fields such as laboratory safety management.

When key points cannot be detected, in order to accurately identify character behavior, we need to combine other characteristics, not just rely on posture estimation results. However, the introduction of non-skeletal posture features may have an impact on the real-time performance of behavior recognition algorithms. Through the observation of the NTU RGB+D data set, it is found that the camera is installed in a position with a large field of view and can avoid looking down or looking up from a large angle. This good camera position can effectively reduce occlusion, thereby capturing clearer images. Therefore, the requirements for the installation angle of the camera are put forward, which can not only meet the needs of real-time detection, but also improve the accuracy of multi-target behavior recognition to a certain extent. After obtaining the model-related data and the test data of the simple scene video, some materials in the laboratory environment were selected to test the algorithm. Using the laboratory abnormal behavior recognition model constructed by the method, the renderings of the abnormal behavior bone extraction of laboratory personnel are shown in Fig. 8.

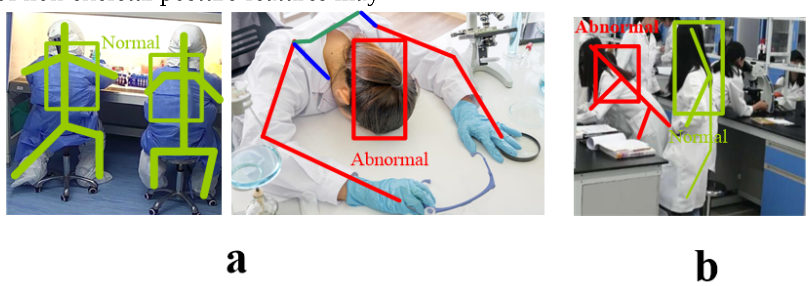

Fig. 8. Recognition effect of the proposed laboratory abnormal behavior recognition model.

As shown in Fig. 8, normal is marked in Fig. 8(a), which indicates the normal laboratory behavior of the experimenter, while abnormal is marked next to Fig. 8(a), which represents the abnormal behavior of the experimenter. In this paper, the proposed method is used to effectively identify the abnormal behavior of laboratory personnel. In Fig. 8(b), the standing position of the experimenter in the laboratory is identified. The algorithm studied in this paper can be well identified for the laboratory behavior of more complex personnel. Normal is marked for normal experimental behavior, while abnormal experimental behavior is marked as abnormal. The proposed method has good motion and posture estimation capabilities, and can accurately detect and track human joints in real time. This allows the model to accurately identify the posture and movements of personnel in the laboratory. At the same time, this method can also achieve multi-person posture estimation, without knowing the specific location of the human body in advance, multiple human bodies can be positioned.

C. Discussion

The obtained results were discussed in the context of previous research findings and methods. Comparative analysis highlights that the proposed method has better performance advantages in detecting abnormal laboratory behavior compared to conventional detection methods. The proposed method focuses on the research of laboratory abnormal behavior detection methods for human skeletal features, which better reduces the interference of complex background environments and other factors in the behavior recognition process. The method uses Kinect sensors to obtain human skeletal feature information, which has a smaller data volume and higher security compared to conventional image data acquisition. The use of moving average filtering, Discrete Fourier Transform, and contrast to preprocess data has improved data quality and recognition performance. Using OpenPose algorithm to achieve fast and stable extraction and classification of behavioral skeletal features. The laboratory abnormal behavior detection model based on skeletal features has higher accuracy and robustness, lower parameter count, and higher operational efficiency compared to traditional laboratory abnormal behavior detection methods.

VII. Conclusions

In recent years, with the continuous deepening of laboratory safety management, effective identification of abnormal behaviors during the experimental process has become one of the current research hotspots. This article takes human bones as the research object, analyzes the characteristics of human bones, and constructs a laboratory abnormal behavior recognition model based on bone features. The model mainly uses OpenPose algorithm and sensor devices to complete behavior recognition. Meanwhile, the model studied in this article mainly analyzes the changes in the spatial trajectory of human skeletal joints, which can effectively identify abnormal behavior in the laboratory. In this study, personnel behavior data was collected in the laboratory, and the YOLOv5 algorithm was used to extract bone features. Then, a laboratory abnormal behavior recognition model was established based on the OpenPose algorithm. The experimental results show that this method can effectively identify abnormal behavior in the laboratory, and performs excellently in accuracy and recall. The main research results obtained are as follows: 1) A model for identifying abnormal behavior can be established, which has a very high accuracy in identifying abnormal behavior; 2) The recognition performance of the constructed model is superior to other models; 3) The recognition model based on OpenPose algorithm can extract human bone feature points more quickly. In summary, the method studied in this article not only has high recognition accuracy, but also has good real-time and stability, which can provide better assistance for laboratory safety management work.

When discussing the superiority and effectiveness of the laboratory abnormal behavior recognition model based on skeletal features studied in this article, it is also necessary to consider its limitations and future improvement directions. The following are several main limitations: Limitations of the dataset: The dataset used in the study may be limited to specific types of laboratory environments and behavioral patterns, thus the model's generalization ability may be limited. Algorithm complexity and computational resources: Although OpenPose algorithm performs well in bone feature extraction and behavior recognition, they have higher computational complexity, which in turn puts higher demands on the hardware resource conditions of the application environment. In the future, further research will be conducted to optimize model performance, enhance model adaptability, and expand the applicability of the model.

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