Intelligent wristband human abnormal behaviour recognition method based on machine vision

Chun-Ling Liu* and Chun-Bao Huo

College of Electrical Engineering,
Liaoning University of Technology,
Jinzhou, Liaoning, China
Email: clliu@mls.sinanet.com
Email: 87003625@qq.com
*Corresponding author

Abstract: In order to overcome the problems of low recognition accuracy and high-recall rate of traditional methods, an intelligent wristband human abnormal behaviour recognition method based on machine vision is proposed. Firstly, the human behaviour video in the smart wristband is obtained through intensive sampling, and the image feature descriptor is obtained according to regularisation processing; the human abnormal behaviour features are extracted by DT algorithm; secondly, softmax classifier is introduced to classify the extracted human abnormal line features of intelligent wristband; the dense trajectory algorithm is used to extract the abnormal behaviour characteristics of intelligent wristband human body, and the machine vision is introduced to recognise the abnormal behaviour of intelligent wristband human body. The experimental results show that the recognition accuracy of this method is as high as 98.2%, and the recognition recall rate is only 4%, which shows that this method can effectively improve the recognition effect.

Keywords: smartband; machine vision; softmax classifier; abnormal behaviour; weighted processing method.

Reference to this paper should be made as follows: Liu, C-L. and Huo, C-B. (2022) 'Intelligent wristband human abnormal behaviour recognition method based on machine vision', *Int. J. Product Development*, Vol. 26, Nos. 1/2/3/4, pp.254–267.

Biographical notes: Chun-Ling Liu received her MD degree in Control Theory and Control Engineering from Liaoning University of Technology in 2002. Currently, she is an Associate Professor in the College of Electrical Engineering of Liaoning University of Technology. Her research interests include machine vision detection and recognition, detection technology and automation device design.

Chun-Bao Huo received his PhD degree in Weapon System and Application Engineering from Beijing University of Technology in 2004. Currently, he is a Professor in the College of Electrical Engineering of Liaoning University of Technology. His research interests include image processing and pattern recognition, machine vision inspection systems.

1 Introduction

Some scholars have proposed the research of identifying human behaviour to intuitively reflect the state of human specialisation in the form of data (Jia and Yang, 2020). With the continuous innovation of various technologies, computer vision technology has become a research hotspot and gradually applied to various fields. This technology simulates biological vision through computers and other scientific equipment to achieve the purpose of rapid collection and processing of visual information (Zhnag et al., 2021). Because this technology has the performance of monitoring, it is applied to the field of human behaviour recognition. Whether it is residential, airport, transportation, bank or shopping mall, it can identify abnormal behaviour through computer data technology, because it can effectively ignore a large amount of data information useless for security in the video, overcome the difficulties of investigation and evidence collection of manually monitored video images, and save manpower and material resources, Promote economic benefits (Su et al., 2019). At the same time, it provides a stable guarantee for people's life and promotes the improvement of living standards, which reflects its important research significance and social value.

At present, there are many ways to obtain human behaviour data (Hu and Guan, 2019), such as visual sensing, which is often used in large monitoring sites, but its high cost, small coverage area and potential safety hazards are not suitable for places with higher requirements. The emergence of wireless communication technology has changed this way. The behaviour recognition method of wearable sensor network has been developed, which has entered the vision of the people. This method obtains human body data by wearing sensors, analyses and processes the data and then judges the motion state.

Luo et al. (2020) proposed a crowd abnormal behaviour recognition method based on deep learning and sparse optical flow, segmented the video into multiple sub regions, obtained the image samples of the sub regions, and detected the small group anomaly that induced the crowd anomaly. The sparse optical flow method was used to obtain the average kinetic energy and motion direction entropy of the crowd, and the obtained characteristic data were classified by pso-elm, Distinguish between normal behaviour and irregular sudden dispersion to realise the recognition of abnormal behaviour. This method has a good recognition recall rate, but the recognition accuracy is low. Guan et al. (2018) proposed an interactive abnormal behaviour recognition method based on neural network. The abnormal behaviour in surveillance video is recognised through deep learning technology, the video data is pre-processed through background subtraction algorithm, the algorithm model is trained on the training data set by deep learning technology, and finally the algorithm model is verified on the test data set, This method can improve the recognition recall rate, but the recognition accuracy is poor. Zhang (2017) proposed a method for identifying abnormal behaviour of network communication. Based on the data as NetFlow network management data, based on the structural similarity between video image frames, combined with illumination induction and illumination compensation mechanism, the background modelling is carried out and the corrected optical flow field and corrected motion history map insensitive to illumination mutation and background motion are obtained to realise the identification method of abnormal behaviour of network communication, This method has a good effect on abnormal behaviour recognition, but the number of iterations is less in a certain time.

To solve the above problems, this paper proposes an intelligent wristband human abnormal behaviour recognition method based on machine vision. The specific implementation ideas are as follows:

- In the first step, the human behaviour video in the smart wristband is obtained through intensive sampling, and the multi-scale space is divided to obtain the human behaviour image. The human abnormal behaviour image feature descriptor is obtained according to the regularisation processing trajectory, and the human abnormal behaviour feature is extracted by DT algorithm;
- In the second step, softmax classifier is introduced to classify the extracted abnormal line features of intelligent wristband human body, and the probability value is normalised to realise the denoising of abnormal line features;
- In the third step, the deviation of 3D pixel discretisation of human abnormal behaviour is eliminated according to the weighted processing method, and the feature vector of human abnormal behaviour is obtained through the combination of point density vector coding; The dense trajectory algorithm in machine vision technology is used to extract the characteristics of human abnormal behaviour of intelligent wristband, and realise the recognition of human abnormal behaviour of intelligent wristband.

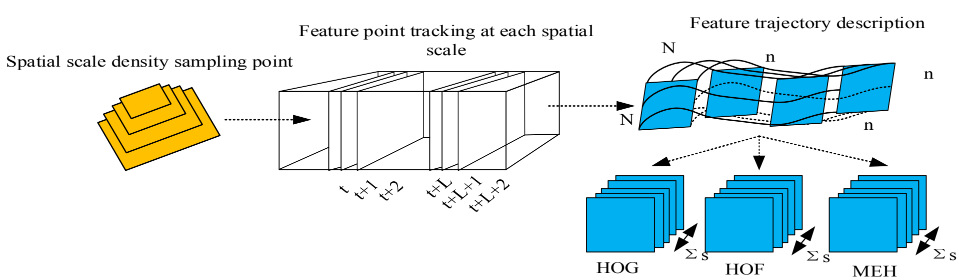
The fourth step is to summarise the full text.

2 Human abnormal behaviour feature extraction

2.1 Intelligent wristband human abnormal behaviour extraction

DT algorithm can collect motion data in video (Liu et al., 2020) and effectively collect surrounding environment information. The flow diagram is shown in Figure 1.

Figure 1 Flow chart of feature extraction



In the process of DT algorithm implementation, the human behaviour video in the smart wristband is obtained by intensive sampling, so as to track the position of feature points, then extract features according to the feature trajectory, and finally encode features. The implementation process of the algorithm is as follows:

Firstly, the collected human behaviour video is divided into 8 scale spaces into one frame, and grid sampling is performed in the scale space (Kai et al., 2020). Generally, the extracted feature points can represent the motion and changes in the image. Therefore, more feature points can be retained in the region with rich image changes, that is, the boundary of the moving target (Tian et al., 2019). Few feature points are retained in the area lacking change. Therefore, it is necessary to calculate the Eigenvalue for removing the feature points lower than the set threshold. The formula for setting the threshold T of DT algorithm is:

$$T = 0.001 \times \max_{i \in I} \min\left(\lambda_i^1, \lambda_i^2\right) \tag{1}$$

Among them, 0.001 is a reasonable value obtained through $\left(\lambda_i^1, \lambda_i^2\right)$ large number of experiments, and a is the characteristic value of pixel i.

In feature point tracking, it is necessary to track the feature points in each scale space. Assuming the I_t image feature point coordinate $p_t = \left(x_t, y_t\right)$, the position of I_t in the next frame can be calculated and recorded as I_{t+1} image.

$$p_{t+1} = \left(x_t, y_t\right) + \left(M * w_t\right)\Big|\left(x_t, y_t\right) \tag{2}$$

where $w_t = \left(\mu_t, \gamma_t\right)$ is the dense optical flow field of feature points, which is the optical flow vector calculated by adjacent frames, μ_t and γ_t are the horizontal and vertical components of the optical flow vector, and M is the median filter. The motion trajectory (Huang et al., 2019) is constructed by formula (16), and its shape can be $\left(p_t, p_{t+1}, \ldots, p_L\right)$. Generally, the trajectory with L as 15 and length L is expressed as $\left(\Delta p_t, \Delta p_{t+1}, \ldots, \Delta p_{t+L-1}\right)$ and displacement vector $\Delta p_t = \left(x_{t+1} - x_t, y_{t+1} - y_t\right)$. After completing the above operations, regularise the track and obtain the image feature descriptor of human abnormal behaviour (including fall, sprain, expression distortion, hand injury, sudden squat and other behaviours).

$$T = \frac{\left(\Delta p_t, \Delta p_{t+1}, \ldots, \Delta p_{t+L-1}\right)}{\sum_{t+l\_1}^{j=t} \Delta p_t} \tag{3}$$

Since L=15 is set, and each frame has displacement vector components in the horizontal and numerical directions, a 30 dimensional feature vector T is obtained. After obtaining the trajectory shape features of feature points, DT algorithm needs to further extract the trajectory features.

2.2 Classification of human abnormal behaviour with intelligent wristband

In the recognition of human behaviour, the sub-softmax classifier is introduced to classify the extracted features.

Suppose that when k actions are classified, the training set is composed of m labelled samples, and the representation of the training set is:

$$T = \left\{\left(x(1), y(1)\right), \ldots, \left(x(m), y(m)\right)\right\} \tag{4}$$

where $x(i)$ is the B input sample; $y(i)$ is the sample label, $y(i) \in \{1, 2, \ldots, k\}$.

For a given test input *x*, the function of the classifier estimates each category *j* to obtain the probability value $p(y = j|x)$. Suppose that the function outputs a *k* dimensional vector representing the probability of *k* category estimates, and the sum of the elements of the vector is 1 (Lentzas and Vrakas, 2020). Vector function $h_\theta(x)$ is:

$$h_\theta(x_i) = \begin{bmatrix} p(y_i = 1|x_i;\theta) \\ p(y_i = 2|x_i;\theta) \\ \vdots \\ p(y_i = k|x_i;\theta) \end{bmatrix} \tag{5}$$

wherein $\theta_1, \theta_2, ..., \theta_k$ constitutes the parameter matrix of the model, in which each row corresponds to a parameter of the classifier, and θ is expressed as:

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_k \end{bmatrix} \tag{6}$$

The probability values are normalised so that each value is mapped in the (0, 1) interval, and the sum of the obtained probabilities is 1. At the same time, the value with high probability is taken as the final classification result to realise the denoising of human abnormal line features of intelligent wristband.

2.3 Training of abnormal behaviour characteristics of human body with intelligent wristband

The point density distribution describing the abnormal behaviour of intelligent wristband human body is presented, and each unit is divided into 6×6×6 3D pixels are fast, and a histogram is established for the points in each 3D pixel fast, using 3D Gaussian kernel function:

$$d(x, y, z, k, l, m) = \exp\left(-\frac{(x-k)^2 + (y-l)^2 + (z-m)^2}{2\sigma_d^2}\right) \tag{7}$$

Each point is weighted to eliminate the deviation of 3D pixel discretisation. After obtaining the histogram in the cell, 1000 pairs of them are randomly selected to calculate the difference without pairs, then the difference feature is spliced with the original count histogram and the descriptor captures the first-order and second-order statistics of the point cloud at the same time (Zhou et al., 2021; Li and Li, 2019).

Use the clustering algorithm to generate 50 clustering centres for each of the above types of features, and then encode each feature vector *x* into a 50 dimensional vector $(\vec{f})$, which contains its distance to each centre point:

$$f(i) = e^{-\frac{x - c_j^2}{\sigma_i^2}} \tag{8}$$

where σ_i^2 is the standard deviation of the *i* cluster. Each of the above types of features is encoded, in which the point density vector is encoded as:

$$\left(\overrightarrow{f_{Po\text{int}}}\right)=\left\{f(0),f(1),f(2),...,f(49)\right\} \tag{9}$$

Then, all encoded feature vectors are spliced to form the final human abnormal behaviour feature vector:

$$\left(\vec{F}\right)=\left\{\overrightarrow{f_{Po\text{int}}},\overrightarrow{f_{Shapet}},\overrightarrow{f_{Normal}},\overrightarrow{f_{TSDF}}\right\} \tag{10}$$

Input the feature vector into the classifier for training, get the training of human abnormal behaviour characteristics of intelligent wristband and complete the data pre-processing of human abnormal behaviour characteristics.

3 Intelligent wristband human abnormal behaviour recognition model based on machine vision

The monitoring scene is constructed through Gaussian model, and machine vision is introduced to complete the recognition of human abnormal behaviour characteristics of intelligent wristband (Zhou et al., 2020).

Firstly, determine the centroid (x_c, y_c) of the abnormal motion area of the human body, and the specific calculation formula is:

$$x_c=\frac{1}{N_b}\sum_{i=1}^{N_b}x_i \tag{11}$$

$$y_c=\frac{1}{N_b}\sum_{i=1}^{N_b}y_i \tag{12}$$

where N_b is the total number of boundary pixels and (x_i, y_i) is the number of boundary pixels.

Take *N* points at equal intervals on the closed contour line, and their complex coordinates are as follows:

$$Z=\left\{(x_i-x_c)+j(y_i-y_c)\right\}\ 0\le i\le N-1 \tag{13}$$

where: x_i and y_i are the coordinates of sampling points, $j=\sqrt{-1}$, x_c and y_c are the regional centroid coordinates. The discrete Fourier transform of $z(i)$ is:

$$f(u)=\sum_{i=0}^{N-1}s(i)e^{-j2ui/N} \tag{14}$$

Including: $u=0,1,...,N-1$. $f(u)$ is the Fourier descriptor of the boundary. $f(u)$ means $\left|f(u)\right|e^{j\theta u}$, where

$$\left|f(u)\right|=\sqrt{(x_i-x_c)^2+(y_i-y_c)^2} \tag{15}$$

The above is the amplitude of the spectrum at frequency u; θu is the phase. Since the amplitude of the spectrum is not sensitive to change, the amplitude of the contour Fourier spectrum is selected as the eigenvector:

$$M = \left[\frac{f(1)}{f(0)}, \frac{f(2)}{f(0)}, \ldots, \frac{f(N-1)}{f(0)} \right] \tag{16}$$

According to the properties of Fourier transform, 50 low-frequency components of the descriptor are selected to describe the contour.

The intelligent wristband human abnormal behaviour recognition model is a dynamic input and static output model. The intelligent wristband human abnormal behaviour recognition process can be regarded as TT dimensional image data input as $\{x_0, x_1, \ldots, x_t\}$, and the output vector $\{y_0, y_1, \ldots, y_t\}$ of the fusion cyclic neural network is combined into a single static label y.

Secondly, the machine vision technology is used to train the image set of human abnormal behaviour. The image set contains T_{tr} machine vision images, namely:

$$P\left(\pi, \theta, \varphi \middle| w_{t>T_w}\right) = P\left(\pi, \theta, \varphi \middle| w_{ET_w}\right) \tag{17}$$

Suppose a new unclassified behaviour pattern W, which is a sequence of *T* image frames, is denoted as:

$$W = \left[w_1, w_2, \ldots, w_T \right] \tag{18}$$

Assuming that the cumulative information of abnormal behaviour image frames collected through the smart wristband is w_{Et}, the model similarity is:

$$l_t = \frac{1}{t} \log P\left(w_{Et} \middle| \pi, \theta, \varphi \right) \tag{19}$$

Then define the abnormal measurement function Q_t based on l_t as:

$$Q_t = \begin{cases} l_t & t = 1 \\ (1-\alpha) Q_{t-1} + \alpha \left(l_t - l_{t-1} \right) & t \neq 1 \end{cases} \tag{20}$$

Among them, $\propto$ is the sparse importance of anomaly detection, which is between 0 and 1. After completing the setting of the measurement function, judge whether it is abnormal:

$$Q_t < Th_A \tag{21}$$

Among them, Th_A *t* is the threshold of human behaviour anomaly detection, which is determined according to the actual detection rate and armed police rate. The image frame of abnormal human behaviour of the intelligent wristband judged above is segment *t*.

When weight decays, add a weight decay item $\frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=0}^{n}\theta_{ij}^2$ to the loss function to modify the expression of the loss function as follows:

$$L(\theta)=\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k}1\{y_i=j\}\log\frac{e^{\theta_j x_i}}{\sum_{l=1}^{k}e^{\theta_l x_i}}\right]+\frac{\lambda}{2}\sum_{i=1}^{k}\sum_{j=0}^{n}\theta_{ij}^2 \tag{22}$$

By minimising $L(\theta)$, an available regression model of human abnormal behaviour classifier can be obtained.

$$\nabla_{\theta_j}L(\theta)=-\frac{1}{m}\sum_{i=1}^{m}\left[x_i\theta\left(y_j-py_i\right)\right]+\lambda\theta_j \tag{23}$$

By minimising, we can get the human abnormal behaviour classifier.

Since the monitoring system often captures information for a long time in a fixed place, the background value y_s collected by machine vision in this method specifies the expected value of the $x_s(n)$ value of all previous frames. Suppose to calculate λ : the points in the second-order neighbourhood system of $x_s(n)$ have the same expected value and variance σ^2 . The λ -value can be calculated with the following formula:

$$\lambda=\frac{\sigma_\tau^2}{\sigma_\varphi^2} \tag{24}$$

Among them, σ_τ^2 is the variance of $\left|x_s(n)-y_s\right|$, and σ_φ^2 是 $\sum_{t\in N(s)}\left|x_s(n)-x_t(n)\right|$ is the variance of. The second-order neighbourhood system used here, so the neighbourhood system of each point consists of 4 points, so there are:

$$\lambda=\frac{Var\left\{\left|x_s(n)-y_s\right|\right\}}{Var\left\{\sum_{t\in N(s)}\left|x_s(n)-x_t(n)\right|\right\}} \tag{25}$$

In terms of network parameter training, whether it is the weight parameter of the YOLO model or the weight parameter of the cyclic network structure, the loss function is calculated by the backward regression process of the output y_t at the current time t according to the input at the current time and the output at the previous time. Yes so for the new $da\left(x_t, y_{t-1}\right)$ ta set *D* that is reconstituted with the data set and the recognition result.

$$\left(x_t, y_{t-1}\right)_{t=1}^{T}\in D \tag{26}$$

Finally, the weight parameter *V* calculated by convolution neural network is used to calculate the weight adoption number by batch random gradient descent algorithm. The human abnormal behaviour recognition function is constructed according to the human abnormal behaviour feature weight parameter *V*, the image feature weight adoption number W and the multi-dimensional vector *F*.

$$L(V,W,F)=\frac{1}{F}\sum\left(x_t,y_{t-1}\right)_{t=1}^{T}\sum_{t=1}^{T}\log P\left(y_t\left|x_t,y_{t-1},V,W\right.\right) \tag{27}$$

According to the objective function *L* in the above formula, a reverse regression algorithm is used to calculate the weight parameters *V* and *W* in the input data set *D* of each batch through the gradient $\nabla_{V,W}L(V,W,F)$.

The data processing flow of the model for human abnormal behaviour recognition is to decompose the video into a t-length image sequence according to each frame, and then input the image into the convolution grid as RGB data. Each image is connected through time factor. The recognition of human abnormal behaviour is completed by the Yolo structure. In the process of image processing, the Yolo model will automatically adjust the image size, so it only needs to normalise the image and input it into the network to realise the recognition of human abnormal behaviour.

4 Analysis of results

4.1 Lab environment

The basic environment for experiment execution is as follows, processor: Intel(R)Core(TM)i7-7700HQ CPU@2.8 GHZ, memory: 16 G, graphics card: GTX1060 6 GB, programming language: python 3.6, development tools: Anaconda3, spyder.

4.2 Evaluating indicator

1) *Recognition accuracy rate*: The recognition accuracy rate g_e represents the proportion of correctly predicted samples among the positive samples in the recognition process, and its calculation formula is:

$$g_e=\frac{R_p}{k_p} \tag{28}$$

In the formula, R_p represents the correct number of human abnormal behaviour recognition, and k_p represents the number of human abnormal behaviour recognition.

2) *Recognition recall rate*: the higher the recognition recall rate of human abnormal behaviour, the better the recognition effect. On the contrary, the lower the recognition recall rate of human abnormal behaviour, the worse the recognition effect.

3) *Number of identification iterations*: The number of iterations completed within the specified time reflects the identification efficiency of human abnormal behaviour. The more identification iterations, the higher the identification efficiency of human abnormal behaviour. On the contrary, the lower the identification efficiency of human abnormal behaviour.

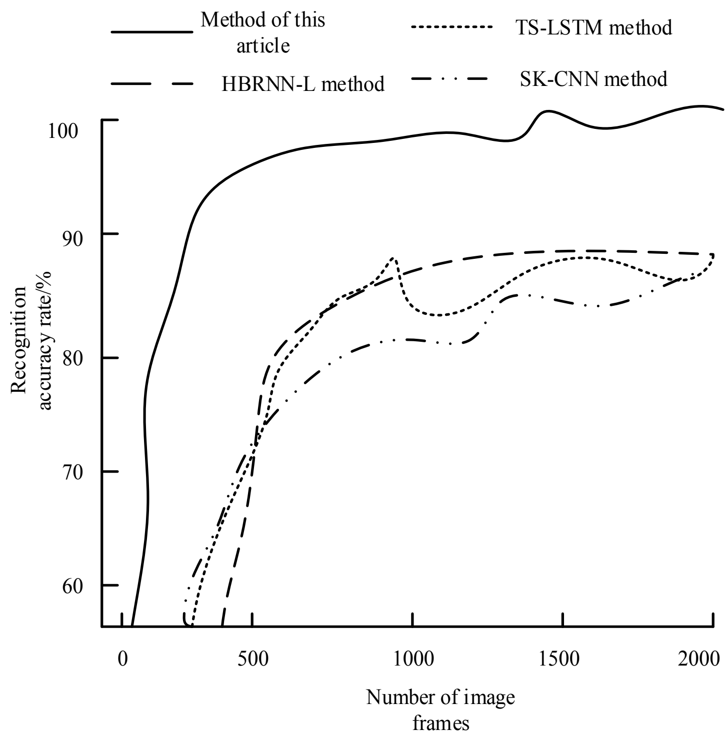
4) *Experimental method*: The feasibility of the design method is analysed, and HBRNN-L method, TS-LSTM method, SK-CNN method and the method in this paper are selected for simulation comparison and verification.

4.3 Result analysis

4.3.1 Recognition accuracy

The effectiveness of the recognition method of abnormal human behaviour is directly affected by the recognition accuracy. Therefore, using the accuracy of human abnormal behaviour recognition as an experimental comparison index, the algorithm in this paper is compared and verified with the HBRNN-L method, the TS-LSTM method and the SK-CNN method. Figure 4 shows the accuracy comparison results of the four algorithms for the recognition methods of abnormal human behaviour.

Figure 2 Comparison of recognition accuracy of different methods

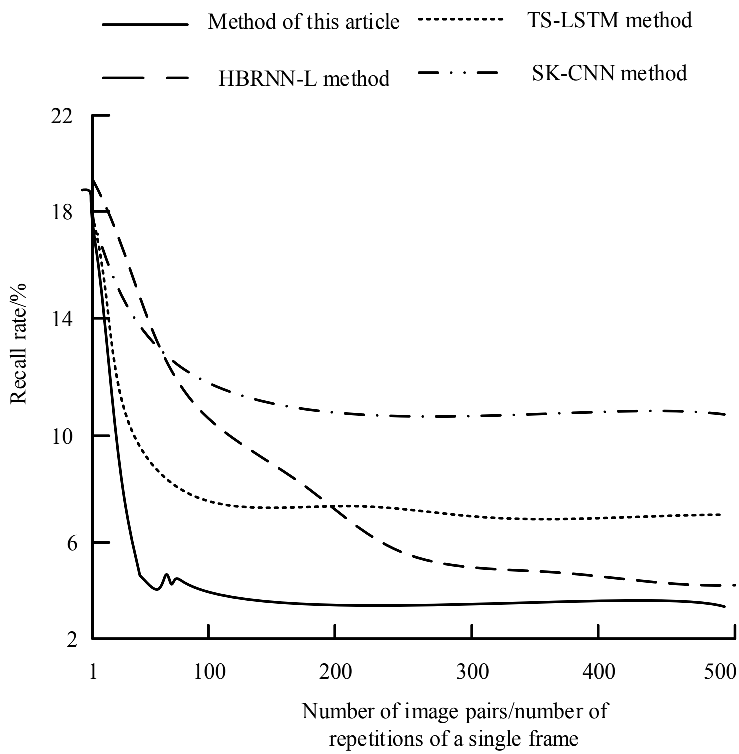


According to Figure 2, the highest recognition accuracy rate using the HBRNN-L method is 88%; the highest recognition accuracy rate using the TS-LSTM method is about 88.2%; the highest recognition accuracy rate using the SK-CNN method is about 86.9%. In the method of this paper, its recognition accuracy rate is up to 98.2%. Compared with the HBRNN-L method, TS-LSTM method and SK-CNN method, the accuracy of this method is much higher than other methods and it has certain advantages.

4.3.2 Identification recall rate

The recognition recall rate of abnormal human behaviour also has serious performance on the recognition performance of the algorithm. If the recognition recall rate is too high, it will reduce the accuracy of the recognition of abnormal human behaviour. Therefore, the human body abnormal behaviour recognition recall rate is selected as an experimental comparison index, and the algorithm in this paper is compared and verified with the HBRNN-L method, the TS-LSTM method and the SK-CNN method. Figure 3 shows the comparison result of the human abnormal behaviour recognition recall rate of the four algorithms.

Figure 3 Comparison diagram of recognition recall rates of different methods



According to Figure 3, the recognition recall rate using the HBRNN-L method is as low as 5%; the recognition recall rate using the TS-LSTM method is as low as 7.8%; using the SK-CNN method, the recognition recall rate is as low as 11.9%; using the method in this paper At this time, the recognition recall rate is about 4%, which is reduced by 1%, 3.8% and 7.9%, respectively compared with the HBRNN-L method, TS-LSTM method and SK-CNN method, which has certain advantages.

4.3.3 Identify the number of iterations

The effectiveness of recognition of abnormal human behaviour is directly affected by the number of iterations. The higher the number of iterations, the higher the efficiency of recognition of abnormal human behaviour. Therefore, using the number of iterations of human abnormal behaviour recognition as the experimental comparison index, the algorithm in this paper is compared with the HBRNN-L method, the TS-LSTM method and the SK-CNN method. Table 1 shows the comparison results of the number of iterations of human abnormal behaviour recognition of the four algorithms.

Table 1 Comparison results of identification iteration times of different methods

Duration/ min	*Method of this article*	*HBRNN-L method*	*TS-LSTM method*	*SK-CNN method*
10	104	63	93	42
20	216	124	186	84
30	432	248	358	168
40	839	483	716	336
50	1573	872	1483	672
60	3921	1693	2831	1344

According to Table 1, the number of identification iterations using the HBRNN-L method is about 580.5; the number of identification iterations using the TS-LSTM method is about 944.5; the number of identification iterations using the SK-CNN method is about 441; using the method in this paper When the number of identification iterations is about 1180.8, compared with the HBRNN-L method, TS-LSTM method and SK-CNN method, it has increased by 600.3 times, 236.3 times and 739.8 times, respectively, indicating that the method in this paper can perform multiple identifications in the same time, which can effectively improve the accuracy of recognition and has certain advantages.

5 Conclusions

In this paper, an intelligent wristband human abnormal behaviour recognition method based on machine vision is proposed. The human behaviour video in the smart wristband is obtained by intensive sampling, and the multi-scale space is divided to obtain the human behaviour image. The human abnormal behaviour feature is extracted by DT algorithm; Softmax classifier is introduced to classify the extracted abnormal line features of intelligent wristband human body, so as to realise the denoising of abnormal line features; According to the weighted processing method, the deviation of three-dimensional pixel discretisation of human abnormal behaviour is eliminated, and the feature vector of human abnormal behaviour is obtained by point density vector coding combination; The dense trajectory algorithm is used to extract the human abnormal behaviour characteristics of intelligent wristband. On the basis of determining the weight threshold, machine vision is introduced to identify the human abnormal behaviour of intelligent wristband. The following conclusions are drawn through experiments:

1) The highest recognition accuracy of this method is 98.2%, which shows that this method has a good recognition effect in the recognition of human abnormal behaviour of intelligent wristband.

2) The recognition recall rate of this method is about 4%, which is 1%, 3.8% and 7.9% lower than HBRNN-L method, TS-LSTM method and SK-CNN method respectively.

3) The number of identification iterations of this method is about 1180.8, which is 600.3 times, 236.3 times and 739.8 times higher than HBRNN-L method, TS-LSTM method and SK-CNN method respectively. It shows that this method can identify multiple times in the same time, can effectively improve the identification accuracy and has certain advantages.

Acknowledgement

This work was supported by Liaoning Provincial Education Department Foundation under grant no. JFL202015401.

References

Guan, B., Bian, C., Feng, S. and Chen, S. (2018) 'Research on interactive abnormal behavior recognition based on neural network', *Electronic Design Engineering*, Vol. 26, No. 20, pp.1–5.

Hu, X. and Guan, Y. (2019) 'Video abnormal behavior recognition method based on 3d-lcrn', *Journal of Harbin Institute of Technology*, Vol. 51, No. 11, pp.71–82.

Huang, Z., Niu, Q. and Xiao, S. (2019) 'Human behavior recognition based on motion data analysis', *International Journal of Pattern Recognition and Artificial Intelligence*, Vol. 34, No. 9, pp.205–215.

Jia, S. and Yang, F. (2020) 'Intelligent recognition method of human dynamic behavior based on neural network', *Science and Technology Bulletin*, Vol. 36, No. 1, pp.60–63.

Kai, Z., Tw, D. and Cw, D. (2020) 'Skeleton based abnormal behavior recognition using spatio-temporal convolution and attention-based LSTM', *Procedia Computer Science*, Vol. 174, No. 8, pp.424–432.

Lentzas, A. and Vrakas, D. (2020) 'Non-intrusive human activity recognition and abnormal behavior detection on elderly people: a review', *Artificial Intelligence Review*, Vol. 53, No. 3, pp.1975–2021.

Li, W. and Li, X. (2019) 'Cluster recognition simulation of abnormal trajectory data in crowd monitoring image', *Computer Simulation*, Vol. 36, No. 2, pp.390–394.

Liu, Y., Zhang, S. and Li, Z. (2020) 'Abnormal behavior recognition based on key points of human skeleton', *IFAC-Papers OnLine*, Vol. 53, No. 5, pp.441–445.

Luo, F., Wang, P., Liang, S., Xu, G. and Wang, W. (2020) 'Crowd abnormal behavior recognition based on deep learning and sparse optical flow', *Computer Engineering*, Vol. 46, No. 4, pp.287–293+300.

Su, B., Zheng, D. and Tang, Q. (2019) 'Human daily short-term behavior recognition method driven by single sensor data', *Infrared and Laser Engineering*, Vol. 48, No. 2, pp.271–279.

Tian, L., Qichao, W.U. and Qiliang, D.U. (2019) 'Recognition of passengers' abnormal behavior on the escalator based on human skeleton sequence', *Journal of South China University of Technology (Natural Science Edition)*, Vol. 47, No. 4, pp.10–19.

Zhang, C., He, N. and Sun, Q. (2021) '3D densenet human motion recognition method based on attention mechanism', *Computer Engineering*, Vol. 47, No. 11, pp.313–320.

Zhang, Y. (2017) 'Dissimilarity analysis of network communication abnormal behavior identification methods', *Microcomputer Application*, Vol. 33, No. 8, pp.79–80.

Zhou, K., Hui, B. and Wang, J. (2021) 'A study on attention-based LSTM for abnormal behavior recognition with variable pooling', *Image and Vision Computing*, Vol. 108, No. 8, pp.104–120.

Zhou, Q., Xing, J. and Yang, Q. (2020) 'Wi-Fi human behavior recognition method based on continuous image depth learning', *Journal of Communications*, Vol. 41, No. 8, pp.43–54.