Track and Field Head Posture Error Correction System Based on Deep Reinforcement Learning

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Abstract. The problem that track and field athletes generally have non-standard postures in their playing actions, a track and field head posture error correction system based on deep reinforcement learning is designed. By optimizing the system configuration, improving the recognition accuracy, using deep reinforcement learning technology to obtain 3D deep dynamic image data of track and field sports, converting the data into quaternion format, storing the data file in VBH format, and shaping the data through deep reinforcement learning technology a dynamic three-dimensional model is used to judge whether the track and field posture is standard using the Euclidean distance comparison method. Using the powerful learning ability of deep reinforcement learning, a series of non-linear operations are performed on the input face image, the abstract features in the image are extracted layer by layer, and then the extracted features are used for classification and recognition and error correction. Finally, through actual research, the standardization of the track and field head attitude error correction system based on deep reinforcement learning is proved. The experimental results show that this method effectively improves the accuracy of attitude estimation.

Keywords: Deep strong chemistry · Track and field · Head posture · Error correction

1 Introduction

In track and field competition, the standard posture of track and field athletes not only determines the stable play of track and field ability, but also determines the probability of injury of track and field athletes. The traditional track and field sports posture can only rely on the naked eye of the coach to correct it, but in most cases, a coach is facing a group of track and field players, so that the wrong posture of the team members cannot be corrected in time, so that most of the track and field athletes generally have non-standard movement posture [1, 2]. Therefore, it is proposed to combine the dynamic three-dimensional model with track and field teaching to reduce the pressure of coach teaching and promote the standardization of track and field sports posture. Two problems need to be solved in practical application of head pose estimation: to solve the influence of illumination, occlusion, background and other factors on the recognition accuracy,

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simplify the calculation steps, and improve the speed and accuracy of the system. As deep reinforcement learning has achieved rich results in the field of image processing, and has mature applications in the field of character recognition, face recognition and so on. Therefore, it has important research value to solve the problems of head posture in practical application [2]. In traditional methods, neural network is used to design track and field head posture error correction system and deep learning is used to design track and field head posture error correction system. However, these two systems have the problem of non-standard play posture. In order to solve this problem, this paper proposes a head posture estimation method based on deep reinforcement learning, and applies this method to the track and field head posture error correction system. This method has the following two advantages: the designed deep reinforcement learning structure uses convolution kernels of different scales to extract features from the original face image, which enriches the image feature expression while retaining the original image information, and better Constructing the corresponding relationship model between face pose and head pose has good robustness to interference factors such as illumination and occlusion. The designed deep reinforcement learning structure can effectively reduce the cost of system calculations, making the system more time-sensitive and accurate.

2 Head Posture Error Correction System in Track and Field

2.1 Hardware Configuration Optimization of Head Posture Error Correction System in Track and Field

In the process of designing the track and field head posture error correction system, it is necessary to consider the head posture characteristics of human body for multi-path recognition, which mainly involves the four fields of track and field head pose image feature analysis, processing, feature extraction and pattern recognition. The head posture image of track and field is a local representation method of human motion, which is accumulated from the first frame of head posture image of track and field to the current frame of the motion video sequence, which covers the specific area of the head posture image of the whole track and field, which is the area where the movement occurs. The specific feature mining process of head posture error in track and field is shown in the Fig. 1 below.

Before head posture feature detection in track and field, the acquired image information needs to be preprocessed to filter the noise and provide accurate data for subsequent recognition [3]. The step of detecting human head posture features in track and field is to extract relevant feature points from complex human motion regions. Under occlusion conditions, clear human images can be obtained through morphological processing. Further select the appropriate human body representation method and extract useful motion information from the human body sequence to determine which type of motion the current exercise belongs to.

Starting from the general recognition process, using depth information, the multi-path recognition and monitoring system of human head posture features in track and field is composed of five parts, which are upper computer monitoring system, posture sensor and STM32 sensor. The system is written with VC++ 6.0, and the main frequency of the computer is 1 GHz, the memory is 256 M, and the video memory is 32 m, After

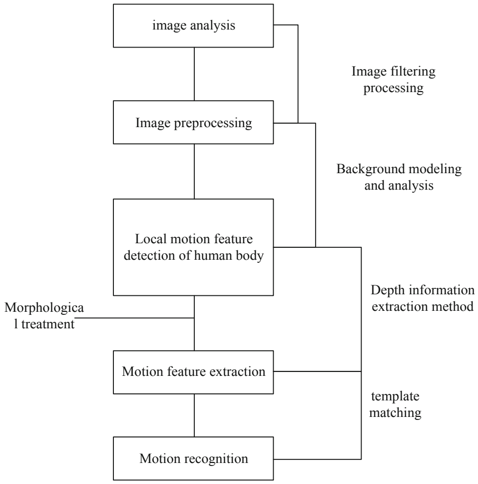

Fig. 1. Mining the characteristics of head posture errors in track and field

the completion of the system, it is handed over to Bailey optical instruments Co., Ltd. for testing, which meets the requirements of the project [4]. The system structure is mainly composed of lpc1788 microprocessor, LCD display control panel, flash, reset module, clock module, power module and wireless transceiver module. The specific hardware structure design is shown in the Fig. 2.

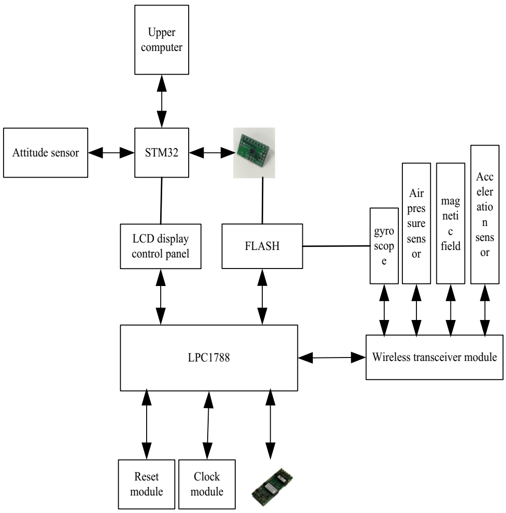

Fig. 2. The main block diagram of the system hardware

It can be seen from the figure that the LPC1788 microprocessor is composed of a 32-bit core high-speed microprocessor of the ARMCortex-M3 model. The maximum operating frequency can reach 150 MHz. The external resources are very rich, including 128 MB of FLASH memory, one for static The external storage controller, LCD display controller, etc., which store external information, and the microprocessor, as the main controller of the human-machine interface, is mainly responsible for controlling each module and realizing the communication function. The controller uses a 6-inch LCD screen with a high resolution of 565RGB mode and a 40-pin digital interface [5]. The LCD display controller is built into the interface, which includes the data bus for image transmission and necessary control signals such as LCD DCLK, LCD ENAB M [6]. Using the touch screen to display the control screen can achieve simple operation in the Internet of Things environment. The display and refresh are displayed on the screen. The system needs to have enough memory space to store complete data. For this reason, need to expand the memory capacity in the design [7]. Based on the original design idea, the wireless module adds the power amplifier function, which can amplify the maximum output power of the wireless module through the power amplifier circuit, and receive the increased signal strength through the LAN circuit, which can effectively increase the communication distance of the wireless module.

2.2 Software Processing Algorithm of Head Posture Error Correction System in Track and Field

Combining deep reinforcement learning methods to optimize the software processing algorithm of the track and field head posture error correction system. Since the training data contains the true value of the head position and head posture, a set of true head position and head orientation vectors can be marked during training. The specific marking points of the head position are different. Based on this, the head posture and marking values of the track and field are standardized, as follows (Fig. 3):

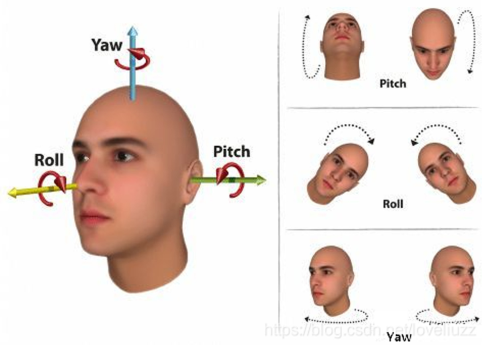

Fig. 3. Head posture and marked value of track and field

In the figure: Q_1—nose tip position, Q_2—A point along the head toward the vector starting from the nose tip point; Q_3—The center point of the sample sub domain image, S_1—sample sub domain sampling range, S_2 and S_3 random rectangle for calculating decision function. Using the labeled head position and head orientation vector, F_1 and

F_3 are saved in the sampling sub domain of depth data. Assuming that $\boldsymbol{\theta}$n is a Gaussian random distribution of three variables, the labeled true value of set P can be expressed as follows:

$$p(\boldsymbol{\theta}_n) = N\left(\overline{\theta}_n, \Sigma_n\right) * \begin{cases} \mathrm{F}_3, \mathrm{F}_2, \mathrm{F}_1 \\ \mathrm{S}_3, \mathrm{S}_2, \mathrm{S}_1 \\ \mathrm{Q}_3, Q_2, Q_1 \end{cases} \tag{1}$$

Thus, the corresponding differential entropy can be calculated for n ∈ {1, 2} :

$$H(P)_n = \frac{1}{2} p(\theta_n)\left((2\pi \mathrm{e})^3 |\Sigma_n|\right) \propto |\Sigma_n| N\left(\overline{\theta}_n, \Sigma_n\right) \tag{2}$$

The regression metric function is the sum of the entropy of all parameters:

$$H_x(P) = H(P)_n \sum_n a_n p(\theta_n) g_{1\mathrm{c}}(\phi)(|\Sigma_n|) \tag{3}$$

In the formula, a_n is the weighting coefficient of parameter correlation, and Σn is the variance matrix. The regression measurement function is substituted into the information gain $g_{1c}(\phi)$ to maximize it, even if the covariance of the Gaussian distribution calculated by all the label vectors θn of the child nodes is minimized, the uncertainty of the regression can be reduced. Mark the category probability as $p(c = k|P)$, and save the distribution of continuous head pose parameters $p(\theta_1)$ and $p(\theta_2)$, where k is the feature category. The calculation of the distribution is carried out by using the image blocks that reach the sub-domain of the training sample, which will be used in the calculation of head pose estimation in the following part [8]. In order to make the relationship between the calculation objects more general and reduce the estimation variance. The selection of the best decision function comes from a set of randomly generated decision function sets $\phi'' = \{\phi\}$. All sample subdomain image blocks arriving at this node must be evaluated by all decision functions in this set, so that the information gain of this node is split The maximized decision function is used as the split decision function of the current node:

$$\phi^* = \arg H_x(P) \max g_{1G}(\phi) \tag{4}$$

The information gain is further defined

$$g_{\mathrm{IG}}(\phi) = H(P) - \omega_{\mathrm{L}} H(P_{\mathrm{L}}(\phi)) - \omega_{\mathrm{R}} H(P_{\mathrm{R}}(\phi)) \tag{5}$$

Where ω_{L} and ω_R are the ratios of the image blocks arriving at the left/right sub nodes to the total training sample set; $H(P)$ is an entropy like metric function of the image block set P in the sample sub domain [9]. In the training process, according to the optimal decision function saved by the node, the data enters into the left/right sub node, and the whole training process goes on iteratively. The stop condition of iteration is that the maximum tree depth specified in the decision tree is reached, or the number of remaining training samples is lower than the specified minimum value. The remaining points after filtering are finally created the cloth is used to estimate the nose tip position θ_1, that is, by adding the average deviation $\overline{\theta}_1$ to the center θ(P) of the image block, the distribution of the nasal tip position is obtained. According to the statistical average diameter of the human head, all the votes are clustered and analyzed, and further optimized by meanshift to remove those outliers. The multi-path recognition of head posture features of track and field sports is carried out. The specific head posture recognition process is shown in the Fig. 4.

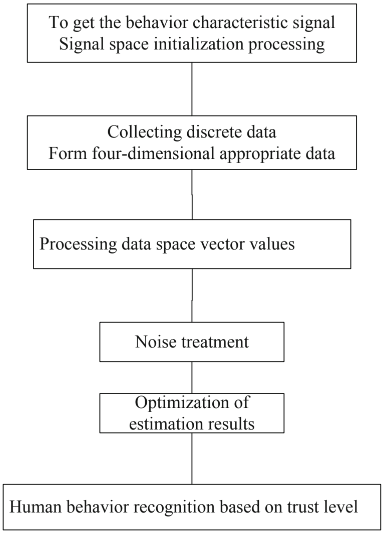

Fig. 4. Head posture recognition steps of track and field

According to the recognition process shown in the figure, the trust level of each component of the data space can be set, and each level can be de-aired to obtain the optimal feature data. The sum of the Gaussian distribution of the head cluster is a new multivariate Gaussian distribution, the mean value as the estimated value of the head posture, the covariance is used as the estimated confidence to calculate and identify the wrong head posture of the athlete.

2.3 Correction of Head Posture Errors in Track and Field

In order to extract multiple features that can predict the deflection angle of the head in the input image, different convolution kernels are needed for convolution operation [10]. The convolution operation can be expressed as follows:

$$\begin{aligned} x^j &= \mathrm{x}^i \min(0, \mathrm{a}^j + \sum u^{\bar{q} \neq x\mathrm{i}}) \\ y^j &= \mathrm{y}^i \max(0, b^j + \sum u^{\bar{q} \neq x\mathrm{i}}) \end{aligned} \tag{6}$$

Among them, x^{i} and y^i respectively represent the i input feature map and the j output feature map; $u^{\bar{q} \neq x\mathrm{i}}$ is the convolution kernel between the q input feature map and the j output feature map, a^j represents convolution, and b^{j} is The offset term of the j output graph. In order to avoid insufficient expression ability of the linear model, it is usually necessary to perform a nonlinear operation on the feature map obtained after convolution to prevent overfitting. Use unsaturated nonlinear functions for hidden layer neurons. Due to the principle of local correlation of image, through down sampling the image, the dimension of the feature map is reduced while retaining the useful information of the image. The operation of single feature map mainly includes average pooling down sampling and maximum pooling down sampling. Average pooling down sampling takes the average value in the neighborhood as the output, and the maximum pooling down sampling takes the maximum value in the neighborhood as the output. The depth learning principle is used to sample the head pose features.

$$z_{j,k}^{i} = \max_{0 \leq m,n \in s}\left\{y^{j} x_{j \cdot s} + m, x^{j} k * s + n^{i}\right\} \tag{7}$$

Among them, $x_{j \cdot s}$ represents the j output spectrum in the down-sampling process, and each neuron is sampled from the s × s local area in the i input spectrum, and m and n respectively represent the step size of the down-sampling frame movement. Soft Max regression is expanded on the basis of logistic regression, mainly to solve multi-classification problems, and is a supervised learning algorithm. The last layer of the network is the Soft Max function, which is used in conjunction with deep reinforcement learning to distinguish the angle category of the input image.

$$F_i = \frac{z_{j,k}^{i} \exp\left(y^{j}\right)}{b_j \sum_{j=1}^{n} \exp\left(x^{j}\right)} \tag{8}$$

Where: $b_j = \sum_{i=1}^{128} x_i \cdot w_{i,j} + b_j$ is a linear combination of 128 features, and the optimization goal of the whole network is to minimize. After obtaining the three-dimensional movement posture data of track and field athletes by deep reinforcement learning technology, these data can be effectively stored and used to drive the dynamic three-dimensional model movement. The storage format of action data is very important. The commonly used storage formats of dynamic 3D model data include rotation matrix, Euler angle and quaternion. The comparison of the three data formats is shown in the table. Based on this, the rotation matrix, Euler angle and quaternion of head posture are standardized. The details are as follows (Table 1):

According to the application comparison of the data storage format in the above table, the quaternion has more advantages than the other two storage formats. Therefore, the 3D dynamic data collected from the deep reinforcement learning is converted in quaternion format. After the data conversion, BVH format is used to store the files. BVH is a common format of action data file, which has the function of import and export, and it is easy to edit and change, and it is convenient to recognize and correct the small posture of head features. Because the dynamic 3D model is established to standardize the standard of track and field posture, a method of comparing the posture of track and field is needed to compare the standard of track and field posture in the model. This time, the European distance comparison method is adopted. The method is to form a threshold value by comparing the track and field posture with the distance of

Table 1. Head posture rotation matrix, Euler angle, quaternion specification parameters

Function	Rotation matrix	Quaternion	Euler angle
Can it be converted into 3D coordinate rotation point	It can't be converted to 3D coordinate rotation point directly, but it needs to be converted to matrix first	can	It can't be converted to 3D coordinate rotation point directly, but it needs to be converted to matrix first
Can rotation be connected	Generally not	can	Generally not
Can interpolation be done	No	can	can
Conversion difficulty	Hard	Easy	Hard
Memory usage	6 numbers	8 numbers	9 numbers
Is the representation of a given mode unique	yes	There are many expressions in the same direction	yes
Can the stored data be used illegally	Illegal use of data may occur	can't	Due to errors, illegal use of data may occur

each joint in the standard sports posture in the model. The smaller the threshold is, the more regional the track and field posture standard is. The formula is as follows:

$$D = F_i \mathrm{sqrt}(x_1 - x_2) + (y_1 - y_2) + (z_1 - z_2) \tag{9}$$

In formula (1), D represents the absolute distance between two track and field posture joints, and the three-dimensional coordinates of the two points are $\mathrm{A}(x_1, y_1, z_1)$, $\mathrm{B}(x_2, y_2, z_2)$ respectively. Then the two track and field posture thresholds T are:

$$T = sqrtD \sum A - B \tag{10}$$

The threshold T is the absolute distance of all joints in two track and field postures. When the T value is larger, it means that the posture of track and field is not standardized, so as to standardize the posture standardization of track and field, and ensure the effective correction of head posture error.

3 Analysis of Results

In order to verify the operation effect of the track and field head posture error correction system based on deep reinforcement learning, experiments were carried out. The experiments were mainly carried out on the CAS-PEAL data set. CAS-PEAL is a data set commonly used for head pose estimation. On this data set, the head pose is divided into 7 discrete angles $\{-45°, -30°, -15°, 0°, 15°, 30°, 45°\}$ in the yaw direction and

3 discrete angles in the pitch direction {−30°, 0°, 30°}. For each picture, use a head gesture recognizer to locate the face area of the picture, intercept the face picture and normalize it to 32*32. Some sample pictures in CAS-PEAL are shown in the Fig. 5:

Fig. 5. Head pose image sample

The experiment was carried out on a subset of CAS-PEAL dataset with object number 401 $\sim$ 600. There are a total of 4200(21 $*$ 200) images on the data subset, and 4166 face images are detected by head pose recognizer. The experimental data set is divided into three data subsets, one of which is used for testing and the other two for training. In this way, all training pictures and test pictures are not crossed. Repeat the experiment three times to make each subset participate in the test. The experimental results are the average of the three test results. On the experimental data set, the experimental results are shown in the table. (Among them, VoD and kVoD use the track and field head posture error correction system based on neural network and the track and field head posture error correction system based on deep learning) (Table 2).

Table 2. Accuracy test results of head posture recognition system in track and field.

	VoD	kVoD	The system of this paper
Error value	4.2	3.9	0.8
Time consuming (min)	8.2	5.6	1.0

Based on the analysis of the detection results in the above table, it can be seen that compared with the traditional two systems, the track and field head posture error correction system based on deep reinforcement learning proposed in this paper has relatively higher recognition accuracy for head posture errors in the actual application process. The time-consuming is shorter. The experimental results show that as the number of objects in the experimental data set increases, the more representative information is contained in the data set. Under the same network structure, the classification accuracy of the test images gradually increases, and the average absolute error slowing shrieking. Further compare the correction effects of the three systems under the noise interference environment and record them, as shown in the Fig. 6 below:

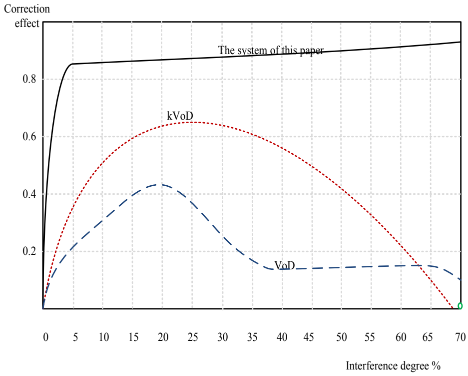

Fig. 6. Comparative detection of system correction effect.

Based on the analysis of the above detection results, compared with the traditional two systems, the head posture error correction system based on deep reinforcement learning proposed in this paper has a better correction effect on the head posture error of athletes in the actual application process, and the system operation is always stable in the case of interference. The experimental results show that compared with the existing correction system, the system has a better effect on correcting the head posture error of athletes. The system has good robustness and accuracy, and can better meet the requirements of practical application.

4 Concluding Remarks

A head pose estimation method based on deep reinforcement learning is proposed. Extracting features through the deep network and classifying and predicting them can significantly reduce the error of attitude estimation on the CAS-PEAL data set, and achieve better experimental results. But the generalization ability of this method depends on the diversity of training data and the complexity of the network structure. The next step is to integrate multiple data sets to train a more complex network structure, and increase the generalization ability of the network structure on the premise of ensuring a lower attitude angle error.

References

1. Burch, A.: From passion to patent: raytheon track-and-field coach inspires STEM in sports [pipelining: attractive programs for women]. IEEE Women Eng. Mag. **12**(1), 28 (2018)

2. Gurioli, L., Di Muro, A., Vlastélic, I., et al.: Integrating field, textural, and geochemical monitoring to track eruption triggers and dynamics: a case study from Piton de la Fournaise. Solid Earth **9**(2), 431–455 (2018)
3. Wu, G., Chen, F., Pan, X., et al.: Using the visual intervention influence of pavement markings for rutting mitigation–part I: preliminary experiments and field tests. Int. J. Pavement Eng. **20**(5–6), 734–746 (2019)
4. Zmitri, M., Fourati, H., Vuillerme, N.: Human activities and postures recognition: from inertial measurements to quaternion-based approaches. Sensors **19**(19), 4058–4059 (2019)
5. Long, T., Liang, Z., Liu, Q.: Advanced technology of high-resolution radar: target detection, tracking, imaging, and recognition. Sci. China Inf. Sci. **62**(04), 1–26 (2019). https://doi.org/10.1007/s11432-018-9811-0
6. Xu, Y., Hou, Z., Liang, J., et al.: Action recognition using weighted fusion of depth images and skeleton's key frames. Jisuanji Fuzhu Sheji Yu Tuxingxue Xuebao/J. Comput. Aided Des. Comput. Graph. **30**(7), 1313 (2018)
7. Wang, B., Liu, D., Wang, W., et al.: A hybrid approach for UAV flight data estimation and prediction based on flight mode recognition. Microelectron. Reliab. **84**, 253–262 (2018)
8. Liu, S., Bai, W., Zeng, N., et al.: A fast fractal based compression for MRI images. IEEE Access **7**, 62412–62420 (2019)
9. Fu, W., Liu, S., Srivastava, G.: Optimization of big data scheduling in social networks. Entropy **21**(9), 902 (2019)
10. Liu, S., Liu, D., Srivastava, G., Połap, D., Woźniak, M.: Overview and methods of correlation filter algorithms in object tracking. Complex Intell. Syst. (2020). https://doi.org/10.1007/s40747-020-00161-4