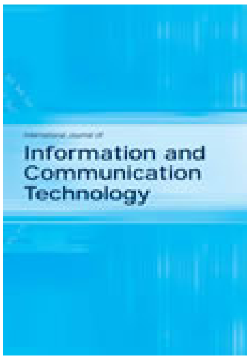


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Study on a method for capturing basketball player's layup motion based on grey level co-occurrence matrix

Luojing Wang

DOI: 10.1504/IJICT.2022.10047495

Article History:

Received:	24 September 2021
Accepted:	08 December 2021
Published online:	05 December 2023

Study on a method for capturing basketball player's layup motion based on grey level co-occurrence matrix

Luojing Wang

Shangqiu Polytechnic,
Shangqiu, 476000, China
Email: luojing@mls.sinanet.com

Abstract: In the process of basketball players' layup motion capture, the image blur leads to high layup motion capture error. Therefore, a basketball player layup motion capture method based on grey level co-occurrence matrix is proposed. The hue, saturation and brightness components of basketball player's layup action image are unified greyed, and the fuzzy information in the image is transformed into different greyscale information. The Pearson correlation coefficient is used to analyse the correlation between each component after greying, and the grey information of fuzzy image is filtered by establishing grey co-occurrence matrix. By analysing the change of positioning coordinates of basketball players' layup action in three-dimensional space, the core area of action capture is determined, and the key point position capture results are aggregated to realise the capture of basketball players' layup action. The results show that the accuracy of the proposed method can reach 97.14%.

Keywords: grey level co-occurrence matrix; motion capture; grey processing; Pearson correlation coefficient; blur image; positioning coordinates.

Reference to this paper should be made as follows: Wang, L. (2024) 'Study on a method for capturing basketball player's layup motion based on grey level co-occurrence matrix', *Int. J. Information and Communication Technology*, Vol. 24, No. 1, pp.60–71.

Biographical notes: Luojing Wang received his Bachelor's degree in Physical Education Major from Shangqiu Normal University in 2009. Currently, he is a University Lecturer at Shangqiu Polytechnic. His research interest is physical education.

1 Introduction

With the rapid economic development and the steady improvement of people's living standards, people are paying more and more attention to the development of the sports industry and the development prospects of sports. Against this background of development, the sports industry has also achieved rapid development and gradually matured (Longman et al., 2020). As a skillful and antagonistic sport, scientific training and accurate movement output is the key to improve the ability of athletes (Zhang et al., 2019). The traditional training process can not target the dynamic layup movement and pointed out that the basketball players can not be used to correct and adjust their movements in time. In this case, the action capture technology can better obtain the basketball players' layup movements, by analysing the captured action data, improve the training methods, and adjust the training concept in time. In order to improve the degree of standardisation of athletes' movements in training, capturing their movements and analysing the captured results with high precision has become a mainstream application trend (Li et al., 2021). It is noteworthy that in the modern era of rising technology, the capture method of fine movements is more and more advanced, and the evaluation and analysis of movements only by human eyes can not meet the needs of high precision training at present (Danial et al., 2019). Therefore, many experts and scholars began to devote themselves to the research of motion capture.

Kreyenmeier et al. (2020) used the high-precision capture of the participant's movements to focus on the preparation process of their eye and hand movements. According to TVA, the image data is modelled to evaluate the overall attention ability and the position of visual attention in the actual movement process. However, because the data collection process is cumbersome, the effect of visual analysis of the movement is reduced. Murgia et al. (2019) described the interaction between complex movement and perception, and studied the behaviour in sports, from movement perception to actual movement behaviour. Through the role of visual information in the perception and execution of complex sports, it can improve actual performance. Sports behaviour: Morimoto (2020) proposed a new accurate and high-speed measurement method, which captures the motion through raster projection to determine the phase of each point on the motion image. This method can capture human motion in real time, and capture the actual situation through free vibration modal analysis images. From this, we can see that it is necessary to study the motion capture method. Grey level co-occurrence matrix, as a high-precision recognition technology (Zhu et al., 2020), cannot only reduce the blurring problem caused by low image quality, but also embody the information in the image in a way of simpler grey level, which is helpful to improve the effect of motion capture method.

Based on this, this paper proposes a research on basketball players' layup motion capture method based on grey level co-occurrence matrix. The Pearson correlation coefficient is used to analyse the image component characteristics and establish the grey level co-occurrence matrix. The change of target position information in three-dimensional space is determined by matrix to capture the action. The technical route of this paper is as follows:

1. according to the unified grey processing of the hue, saturation and brightness components of the basketball player's layup action image, the fuzzy information in the image is transformed into different grey information
2. Pearson correlation coefficient is used to analyse the correlation between each component after greying, and the grey information of fuzzy image is filtered by establishing grey co-occurrence matrix
3. on this basis, by analysing the change of positioning coordinates of basketball players' layup in three-dimensional space, determine the core area of action capture, gradually migrate from the local planning scope to the transition area, and aggregate the key point position capture results to realise the capture of basketball players' layup.

2 Establishment of grey level co-occurrence matrix

2.1 Image greying

In general, colour space exists as colour model in motion capture images. Although this model can calibrate the motion information with high precision, the generated colours can also help to divide the background of the captured object more clearly (Sudharshan and Rahul, 2020). In view of this, this article through the establishment of grey co-occurrence matrix for the image to develop a new set of standard rules and definitions, the use of its realisation of the layup action capture. Grey level co-occurrence matrix is a method that can process the hue, saturation and brightness of the image to improve the quality. This method has high precision and efficiency. Therefore, this paper uses this algorithm to process the image.

The colour space includes three components: hue (*H*), saturation (*S*) and luminance value (*V*). Among them, *H* represents attributes. When the unified greyscale processing of an image is carried out in this paper, red is taken as the benchmark, which is defined as 0°, corresponding green is 120° and blue is 240° (Razavikia et al., 2019); *S* represents purity, which is described by the distance from the central axis in this paper, and the farther away from the central axis, the higher saturation is defined; and brightness *V* represents brightness, which is 0. On this basis, the greyscale processing of the original image can be represented as follows:

$$D' = \begin{cases} (G-B)\dfrac{D_{\max} - D_{\min}}{240} \\ (B-R)\dfrac{D_{\max} - D_{\min}}{240} \\ (R-G)\dfrac{D_{\max} - D_{\min}}{240} \end{cases} \tag{1}$$

Among them, D' represents the grey-processed image, and $D_{\min}$ and $D_{\max}$ represent the highest and lowest values of the described components in the original image, respectively. On this basis, the image is divided into different intervals:

$$B = \begin{cases} 0, & D_{\max} = D, \\ 1 - \dfrac{D_{\max} - D_{\min}}{240}, & D < D_{\max} < D \\ 1, & D > D_{\max} \end{cases} \tag{2}$$

Among them, *B* denotes the grey image after the interval partition standard.

In this way, the greyed image information is displayed in a more intuitive way. At this time, the smaller the coupling of different description components, the more obvious the distinction and comparison between intervals, which can provide a good basis for subsequent motion capture. In addition, the greyscale colour space target and background segmentation can effectively reduce the interference of fuzziness and improve the robustness of segmentation.

2.2 Greyscale component analysis

After obtaining the greyscale image, the various greyscale components should be analysed to construct the corresponding greyscale symbiosis matrix. This is because the texture characteristics of the image are usually described by the spatial distribution and grey distribution, grey symbiosis matrix can take into account the connection between the two, reflect the index element relationship between the fuzzy image, can describe the texture characteristics in the image, and has important reference value for the analysis of image characteristics (Pantic et al., 2020). To do this, first determine the segmentation threshold. Considering that the influence of illumination factor is obvious after the component of the index in the image, this paper regulates the value of the grey level channel to [0, 250] when determining the segmentation threshold. On this basis, this paper takes the Pearson correlation coefficient as the evaluation criterion to realise the judgement of component correlation in different regions of the image (Djunaidi et al., 2021).

Firstly, the H component and S component of the grey image are quantified, and the range of the Pearson correlation coefficient is defined in [–1, 1]. Then the correlation coefficient ∂_{HS} of the two components can be calculated as:

$$\partial_{HS} = \frac{Cov(H, S)}{\sqrt{D'}} \tag{3}$$

Among them, $Cov(H,S)$ represents the covariance of H and S components. When the correlation coefficient is 0, it means that the two are independent and uncorrelated; the correlation coefficient is 1, which means that the two exist in the form of a completely linear positive correlation, and the correlation coefficient is –1, which means that the two are completely linearly negatively correlated. Form exists.

Correspondingly, the degree of correlation between the H component and V component and between the V component and S component can be expressed as follows:

$$\partial_{HV} = \frac{Cov(H, V)}{\sqrt{D'}} \tag{4}$$

$$\partial_{VS} = \frac{Cov(V, S)}{\sqrt{D'}} \tag{5}$$

Among them, ∂_{HV} and ∂_{VS} respectively represent the correlation coefficient between the H component and the V component and the V component and the S component, $Cov(H, V)$ represents the covariance between the H and V components, and $Cov(V, S)$ represents the V and The covariance between the S components.

Then the grey-level co-occurrence matrix of the image can be obtained as:

$$\begin{bmatrix} 0 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 0 \end{bmatrix} \tag{6}$$

This realises the clarification of the symbiotic relationship among the *H*, *S* and *V* components in the image. Based on this, it provides a basis for the filtering of blurred images.

2.3 Blurred image filtering

The fuzzy image contains a high noise signal, which requires filtering processing. Fuzzy image filtering can effectively filter fuzzy information in the collected image and avoid noise on the positioning during motion capture (Hamid et al., 2021).

It can be seen from the above that in the greyscale processed image, the *H*, *S* and *V* components are in a symbiotic relationship. Under normal circumstances, the absolute value of the correlation coefficient exists in the form of less than 0.1. Therefore, you can use. This feature analyses the co-occurrence matrix of different regions in the image, and calculates the linear relationship between any two components, which is used to identify the fuzzy information in the image.

First, calculate the distribution probability of the co-occurrence matrix in the range where the absolute value of the correlation coefficient is less than 0.1, which can be expressed as:

$$P = \begin{bmatrix} 0 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \cdots & 0 \end{bmatrix} e^{\frac{0.1-x}{2}} \tag{7}$$

Among them, x represents the correlation coefficient between any two components in the co-occurrence matrix.

In this paper, 95% probability is selected as the criterion for fuzzy images. According to the division criteria in the standard normal distribution function table, the corresponding threshold intervals are calculated to be [24, 18, 36] and [55, 5, 9, 116]. According to this standard, the fuzzy information in the image is identified and filtered.

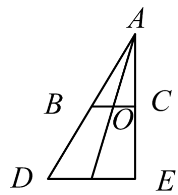
According to the unified greyscale processing of the hue, saturation and brightness components of the basketball player's layup action image, the fuzzy information in the image is transformed into different greyscale information, which lays the foundation for the subsequent basketball layup action capture.

3 Motion capture method

3.1 Space coordinate positioning

Based on the above, the spatial coordinates of the target object in the filtered greyscale image are positioned (Guillaume, 2020). First, establish a conversion relationship between the athlete's coordinate system *O-xyz* and the image coordinate information. Except for the coordinate unit, ensure that the co-mean coordinate components are consistent. Figure 1 shows the mapping relationship between the actual sports coordinates and the athlete's coordinates in the image.

Figure 1 Mapping diagram



Let $l_x = BO$, $l_y = CO$; $l_u = BC$, $l_v = DE$, then by establishing the mapping relationship between (l_x, l_y) and (l_u, l_v), the mapping relationship between BC and DE can be obtained indirectly, It can be expressed as:

$$\begin{cases} l_x = l_u \sin\alpha \\ l_y = l_u \cos\alpha \end{cases} \tag{8}$$

Among them, α represents the angle between the image acquisition equipment and the athletes.

In the image acquisition process, there will inevitably be the problem of the loss of target depth information (Wu et al., 2021), and because the coordinates of the athlete in the image are in the same plane as the actual ground, there is a certain amount of direct calculation of the position information of the athlete through the image coordinates. For this reason, this paper uses the greyscale image segmentation standard to correct the error of the image coordinates, which can be expressed as:

$$\begin{cases} l_x = l_u \sin\alpha + r \\ l_y = l_u \cos\alpha + h \end{cases} \tag{9}$$

In the formula, r is the image acquisition radius, and h is the height of the image acquisition device based on the plane where the athlete is located.

According to formula (8), the athlete's imaging coordinates in the image can be used to realise the coordinate positioning that you can only do in practice.

3.2 Layup motion capture

Considering that in actual situations, athletes' movements are mostly coordinated by the limbs at the same time to coordinate the body's posture changes. For this reason, this article captures the movement changes by setting anchor points on the edges of the athlete's body in the image, and adopts a spiral traversal method. Ways to track the moving path of the anchor point, so as to achieve the purpose of improving the capture efficiency.

First, plan the basic activity range of athletes in the local space of the visual image, and use this range as the core area of motion capture. In order to reduce the impact of regional division on the capture results, the range is divided into local visual inspection standards. Several sub-regions, each of which is used as the basic unit of traversal during motion capture, gradually migrates from the local planning area to the transition area.

$$\begin{cases} x_n = n(n-1)l_x \sin\alpha \\ y_n = n(n-1)l_y \cos\alpha \end{cases} \tag{10}$$

Among them, x_n and y_n respectively represent coordinate information after migration, and n represents a sub-region.

Next, in order to ensure the continuity of motion capture, the traversal law of anchor points is not restricted, that is, a fixed difference relationship between n values is not required. In this way, it is ensured that the changes of each positioning point can be captured in the first time. When the traversal of the current working sub-area is completed, the area migration takes the nearest positioning point in the field of view as the priority selection target. When the anchor point of the basic activity range moves during the process, it is allowed to traverse the current working sub-area. When there is no movement of the anchor point in all the sub-areas, it can be considered that the motion capture of the current sub-work area is completed, and the key points the position capture results are aggregated to get the completed action portrait.

$$F = \frac{\prod x_n y_n}{n} \tag{11}$$

F is the final capture result. At the same time, the traversal re-migrates back to the centre of the sub-area, waiting for the next move of the anchor point, and then capturing again.

In the basketball player's layup action capture, by analysing the change of positioning coordinates of basketball player's layup action in three-dimensional space, determine the core area of action capture, gradually migrate from the local planning scope to the transition area, and aggregate the key point position capture results to realise the basketball player's layup action capture.

4 Experimental analysis

In order to test the actual application effect of the method proposed in this paper, experimental tests were carried out, and the methods of Kreyenmeier et al. (2020) and Murgia et al. (2019) were used as the control group to improve the reliability of the test results.

4.1 Parameters design of the experimental environment machine

Take the two half-field areas as the capture range, and divide the area into 3 m × 3 m sub-areas. The visual image has a radius of 4.5 m and a visual angle of 45°, which is collected from the field circumferential field. Assuming that during the motion capture process, the athlete's behaviour point moves in a straight line with a small distance, regardless of the visual feedback error, the posture and trajectory of the positioning point are accumulated, and at the same time, the change in the angle generated during the posture change is ignored. The layup speed v is 0.1–0.4 m/s, respectively. In this way, the method of Kreyenmeier et al. (2020) and Murgia et al. (2019) and the method of this paper are used to capture the action.

4.2 Experimental index design

According to the setting of the above experimental environment and parameters, the test indicators set in the experiment are the players' layup speed V, and the layup action capture effect and capture accuracy are the experimental indicators when the layup speed V is 0.1–0.4 m/s, respectively.

4.3 Results and analysis

Among them, Figure 2 is the image information collected under the state of 0.1m/s. Based on this, the comparison results of the three methods are compared, and the result is shown in Figure 3.

Figure 2 Image acquisition results at a speed of 0.1 m/s

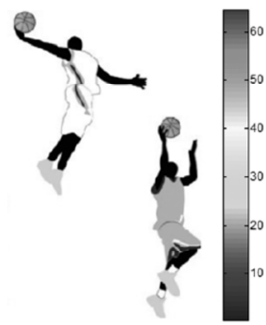
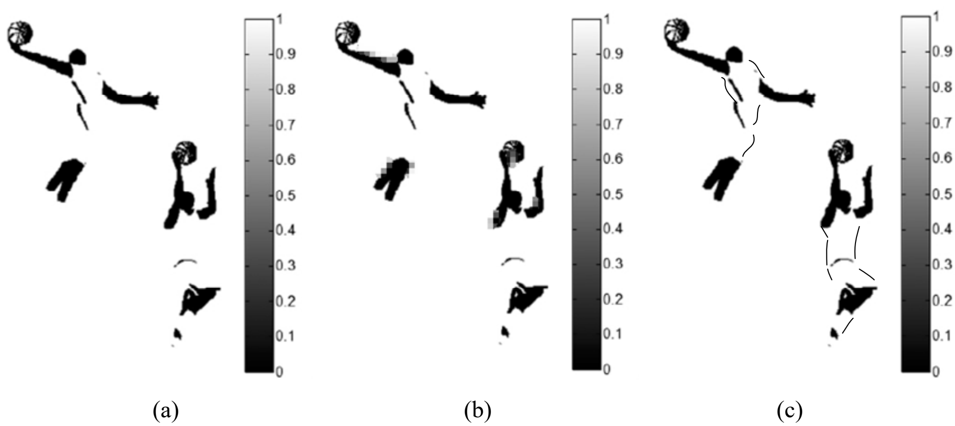


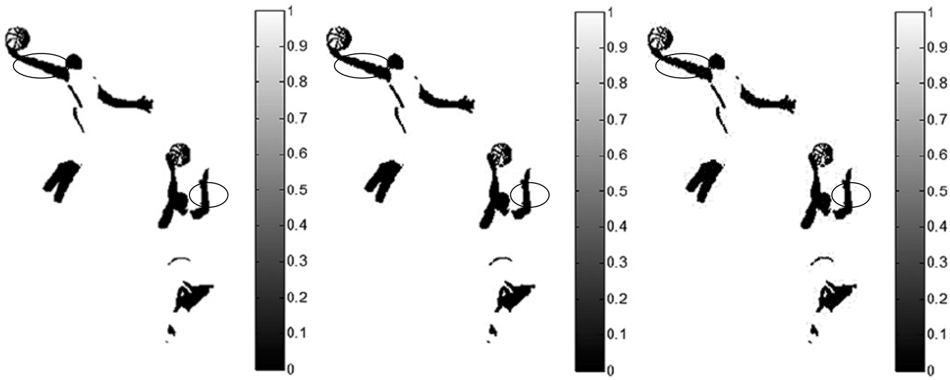
Figure 3 Motion capture test results of different methods, (a) Kreyenmeier et al. (2020) method (b) Murgia et al. (2019) method (c) the method of this paper



It can be seen from Figure 3 that among the three methods, the Kreyenmeier et al. (2020) method can realise the capture of the general movement. In the capture result of the Murgia et al. (2019) method, the edge of the athlete's part of the body is obviously blurred, indicating that the capture appears Inaccurate or unjudgeable action positioning, the capture result of the method in this paper has higher definition and the completeness of the athlete’s action is higher. From the integrity of image capture, this method can completely extract the whole action of task layup in the image, while the capture effect of the other two methods is more general. In contrast, the motion capture effect of this method is better.

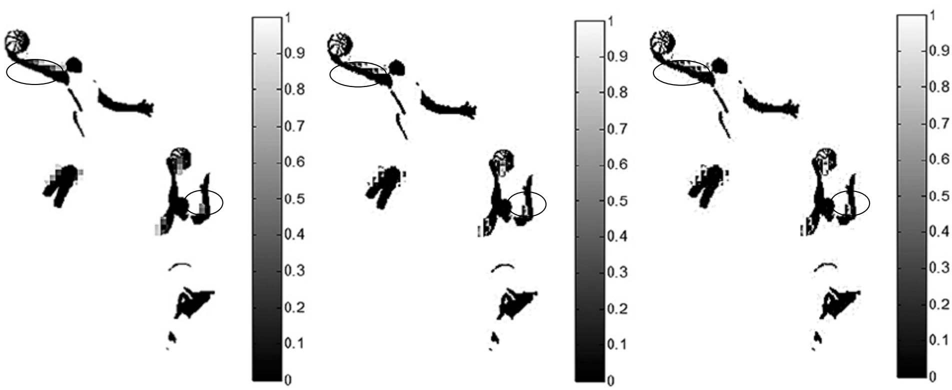
On the above basis, with the increase of the moving speed, the capture results of the three methods are shown in Figures 4, 5 and 6.

Figure 4 The capture results of the Kreyenmeier et al. (2020) method at different speeds, (a) v = 0.2 m/s (b) v = 0.3 m/s (c) v = 0.4 m/s



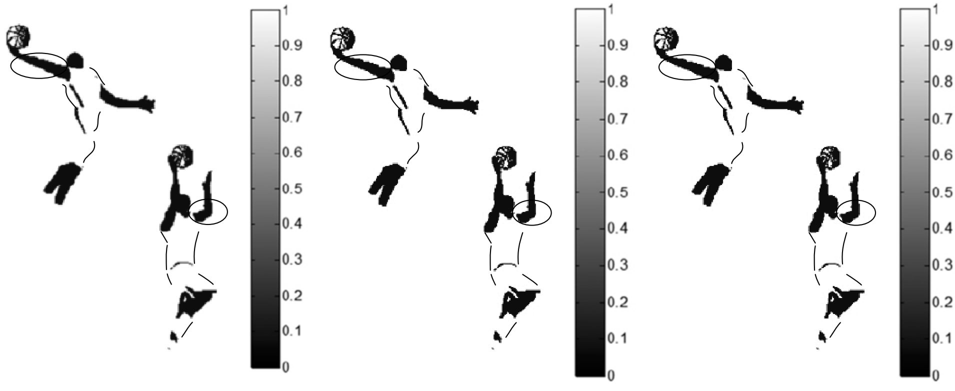
(a) (b) (c)

Figure 5 The capture results of the Murgia et al. (2019) method at different speeds, (a) v = 0.2 m/s (b) v = 0.3 m/s (c) v = 0.4 m/s



(a) (b) (c)

Figure 6 The capture results of this method at different speeds, (a) v = 0.2 m/s (b) v = 0.3 m/s (c) v = 0.4m/s



(a) (b) (c)

By comparing Figures 4, 5 and 6, it can be seen that the capture results of this method are relatively stable, while the capture results of Kreyenmeier et al. (2020) and Murgia et al. (2019) both show a significant downward trend. This is mainly because the method in this paper uses the grey level co-occurrence matrix to filter out the fuzzy information caused by the speed, so the capture result is more stable.

Finally, the accuracy of capturing the athlete's layup motion under different capturing methods is compared, and the results are shown in Table 1.

Table 1 Motion capture accuracy of different methods

Speed (m/s)	*Kreyenmeier et al. (2020) method (%)*	*Murgia et al. (2019) method (%)*	*Method of this article (%)*
0.1	95.26	95.00	97.14
0.2	94.40	90.17	96.78
0.3	89.27	86.39	95.29
0.4	82.03	80.21	95.11

It can be seen from Table 1 that comparing the three methods, the capture accuracy of the methods in Kreyenmeier et al. (2020) and Murgia et al. (2019) gradually decreases with the increase of the athlete's moving speed. When the moving speed reaches 0.4 m/s, its accuracy they are reduced to 82.03% and 80.21% respectively. Although the recognition accuracy of the method in this paper has been reduced to a certain extent, the range is relatively small, and the recognition accuracy has always been maintained above 95%. This is mainly because the method in this paper realises the effective law of blurred images, and the motion capture based on this has higher accuracy.

5 Conclusions

In order to realise the high-precision training of basketball, this paper proposes a method of basketball players' layup motion capture based on grey level co-occurrence matrix. Through the grey processing of basketball players' layup action image, and through the establishment of grey co-occurrence matrix, the grey information of fuzzy image is filtered; On this basis, by analysing the change of positioning coordinates of basketball players' layup in three-dimensional space, determine the core area of action capture, gradually migrate from the local planning scope to the transition area, and aggregate the key point position capture results to realise the capture of basketball players' layup. Compared with traditional methods, this method has the following advantages:

1. using the proposed method to capture the layup of sample basketball players has good effect and certain feasibility
2. the highest accuracy of the proposed method is about 97.14%, which verifies the effectiveness of the method.

The method proposed in this paper provides a valuable reference for athletes' movement analysis. Limited by the research conditions, there is still room for further research. In the future work, we can start from the following aspects:

1. Therefore, with the development of the movement acquisition device, the corresponding movement acquisition method can be made on the basis of the corresponding development of the movement acquisition device.
2. The purpose of motion capture is to provide the basis for subsequent correction and intensive training. In the subsequent research, we can deepen the research on this goal, analyse the captured action by inputting the target action in the algorithm, and directly give the corresponding indicators and methods to be optimised, so as to make it more intelligent and improve its practical application value.

References

Danial, L., Thomas, S. and Kvatinsky, S. (2019) 'Delta-sigma modulation neurons for high-precision training of memristive synapses in deep neural networks', *2019 IEEE International Symposium on Circuits and Systems (ISCAS)*, IEEE.

Djunaidi, K., Agtriadi, H.B., Kuswardani, D. et al. (2021) 'Gray level co-occurrence matrix feature extraction and histogram in breast cancer classification with ultrasonographic imagery', *Indonesian Journal of Electrical Engineering and Computer Science*, Vol. 22, No. 2, pp.795–800.

Guillaume, T. (2020) 'On the telegrapher's equation with three space variables in non-rectangular coordinates', *Journal of Applied Mathematics and Physics*, Vol. 8, No. 5, pp.910–926.

Hamid, M.M., Hammad, F.F. and Hmad, N. (2021) 'Removing the Impulse Noise from grayscaled and colored digital images using fuzzy image filtering', *2021 IEEE 1st International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering MI-STA*, IEEE.

Kreyenmeier, P., Deubel, H. and Hanning, N.M. (2020) 'Theory of visual attention (TVA) in action: assessing premotor attention in simultaneous eye-hand movements', *Cortex*, Vol. 133, No. 26, pp.133–148.

Li, X., Lu, Y. and Chen, Y. (2021) 'Constraining nitrification by intermittent aeration to achieve methane-driven ammonia recovery of the mainstream anaerobic effluent', *Journal of Environmental Management*, Vol. 295, p.113103.

Longman, D.P., Wells, J. and Stock, J.T. (2020) 'Human athletic paleobiology; using sport as a model to investigate human evolutionary adaptation', *American Journal of Physical Anthropology*, Vol. 2020, No. 18, pp.42–59.

Morimoto, Y. (2020) 'High-speed measurement of shape and vibration: whole-field systems for motion capture and vibration modal analysis by OPPA method', *Sensors*, Vol. 20, No. 15, p.4263.

Murgia, M., Agostini, T. and McCullagh, P. (2019) 'Editorial: From perception to action: the role of auditory and visual information in perceiving and performing complex movements', *Frontiers in Psychology*, Vol. 10, No. 31, p.2696.

Pantic, I., Jeremic, R. and Dacic, S. (2020) 'Gray-level co-occurrence matrix analysis of granule neurons of the hippocampal dentate gyrus following cortical injury', *Microscopy and Microanalysis*, Vol. 26, No. 1, pp.1–7.

Razavikia, S., Amini, A. and Daei, S. (2019) 'Reconstruction of binary shapes from blurred images via Hankel-structured low-rank matrix recovery', *IEEE Transactions on Image Processing*, Vol. PP, No. 99, p.1.

Sudharshan, D.P. and Rahul, H.L. (2020) 'Identification and extraction of text in non-blurred and blurred image sequences', *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)*.

Wu, S., Xiao, S. and Di, Y. (2021) '3D film animation image acquisition and feature processing based on the latest virtual reconstruction technology', *Complexity*, Vol. 2021, No. 1, pp.1–11.

Zhang, Y., Sun, Y., Li, X. et al. (2019) 'Training effects of eye movement on improving basic cognitive ability of mild cognitive impairment (MCI) patients and normal aging (NA) people', *International Journal of Sciences*, Vol. 8, No. 6, pp.47–50.

Zhu, L., Dang, F., Ding, W. et al. (2020) 'Coupled X-ray computed tomography and grey level co-occurrence matrices theory as a method for detecting microscopic damage of concrete under different loads', *China Civil Engineering Journal*, Vol. 53, No. 8, pp.97–107.