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RESEARCH ARTICLE

SELECTION OF THE SUITABLE RECEIVING PARTS BY DEEP LEARNING-BASED FEATURE IMAGE ANALYSIS METHOD

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ARTICLE DETAILS

ABSTRACT

Article History:

Received 16 November 2019 Accepted 20 Decmber 2019 Available online 8 January 2020 To comprehensively understand the variations in joints under different suitable ball-receiving situations of football. A deep learning-based K-means clustering feature image analysis algorithm is constructed to study the variations of joints in three different receiving parts of football: (1) while receiving the ball in the air with the medial side of foot, the displacements and angles of knee, hip, and ankle joints; (2) while receiving the bounce ball with the medial side of foot, the displacements and angles of knee, hip, and ankle joints; (3) while receiving the ball in the air with the backside of foot, the displacements and angles of knee, hip, and ankle joints. By qualifying the displacements and angles of the above joints, the accuracy of selecting the receiving parts can be determined. The results show that the deep learning K-means clustering feature image analysis algorithm is accurate in selecting the knee, hip, and ankle joint displacements and angles under different ball-oncoming situations. As for the displacement values of joints while receiving the bouncing ball with the medial side of the foot, receiving the ball in the air with the medial side of the foot, and receiving the ball in the air with the backside of foot, the judgments are close to the standard values. Also, the algorithm shows excellent stability while selecting and calculating the receiving parts. Based on the deep learning K-means clustering feature image analysis, the displacements and angles in the knee, hip, and ankle joints under three different ball-receiving situations are judged and selected, which provides suggestions for football training and promotion.

KEYWORDS

deep learning, football, receive, K-means, cluster

1. INTRODUCTION

Currently, of all the technological and computer developmental achievements, deep learning is an advanced data processing method. It has $made\ a\ significant\ change\ in\ the\ effect\ and\ function\ of\ data\ and\ has\ become$ an important way to capture hidden information [1]. With the improvement of living standards and social progress, football has become increasingly popular among young people. Many people like to play football, which has become their hobby. At present, football has become the well-deserved most popular sport in the world. It is for this reason that football is receiving increasing attention [2]. Since the study of football is difficult and challenging, which requires excellent physical coordination. If the gap between the exercising methods and the standard methods is large, it will bring huge injuries and dangers to the human body [3]. However, the current effects of football coaching and training are unsatisfactory, which is mainly due to the difficulties caused by the lack of standards and effective training and coaching methods [4]. Such a situation has seriously hindered the development of football in China and the cultivation of football talents. Trapping the ball is the core part of football. If the result of trapping the ball cannot be accurately guaranteed, it cannot provide real help for football. This is a huge problem encountered in learning football. If this problem cannot be effectively solved, the practicing efficiency of football players will be low, as well as the progress in football skills [5,6].

Therefore, this study proposes a deep learning K-means clustering feature

image analysis algorithm to investigate the selection of the receiving parts in football. The major contribution of this study is that by using a modified K-means clustering image analysis algorithm, the problems of finding proper receiving parts in football are solved, thereby improving the training methods of football in terms of ball receiving. The study of football is of great significance both at the individual and national level.

In summary, this study explores the K-means clustering feature analysis algorithm of deep learning, thereby analyzing the changes of the joints in different ball-receiving parts by using the algorithm. The research shows that the deep learning-based K-means clustering feature analysis algorithm has outstanding accuracy and stability in analyzing the joint variations of different receiving parts in football. The innovation of this study lies in the combination of football and deep learning-based K-means clustering feature analysis algorithm, through which these two unrelated fields are combined and the results are analyzed. This study is vital for the study of deep learning-based K-means clustering feature analysis algorithm and football. The research results in this study provide certain guidelines for future research. Therefore, the study is of great significance.

2. METHODOLOGY

2.1 Research methods

This study uses deep learning algorithm models and data analysis methods to analyze the motion indicators in football, such as the structure

of the receiving motion of the foot. The sequence of each part of the swinging leg when the foot receives the ball are analyzed, such as the motion sequence of the hip joint, knee joint, and ankle joint and the direction of the force.

2.2 K-means algorithm construction

The K-means algorithm is described as follows:

$$D = \bigcup_{i=1}^{m} C_{i}$$

$$C_{i} \neq (i = 1,2,..., m)$$

$$C_{i} \cap C_{j} = (i, j = 1,2,..., i \neq j)$$

$$J_{c} = \sum_{i=1}^{m} \sum_{k=1}^{n} d(X_{i}, Z_{k})$$
(3)

Where: $D = \{X_i, i = 1,2,3..., n\}$ is the data object in the dataset to be processed, n is the total number of data points. Each clustering must contain all data objects, and the clusters do not intersect.

$$J_{m} = \sum_{k=1}^{c} \sum_{j=1}^{g} q_{j} \mu_{kj}^{m} \| \mathbf{s}_{j} - \mathbf{v}_{k} \|^{2}$$
(5)

Where: c is the category number of clusters, and V_k is the clustering center of the k-th class. The constraints should be satisfied:

$$\mu_{kj} \in [0,1], \quad \sum_{k=1}^{c} \mu_{kj} = 1, \quad 0 \le \sum_{j=1}^{g} \mu_{kj} \le g, \quad \sum_{j=1}^{g} q_{j} = n$$
(6)

In Equation (6), n is the total number of pixels in the image. The μ_{kj} and

 ${\color{blue}V_k}$ of obtaining the minimum value are solved by using the Lagrangian multiplier method. It is assumed that

$$L = \sum_{k=1}^{c} \sum_{j=1}^{g} q_{j} \mu_{kj}^{m} \| s_{j} - v_{k} \|^{2} + \sum_{j=1}^{g} \lambda_{j} \left(1 - \sum_{k=1}^{c} \mu_{kj} \right)$$
 (7)

It can be obtained from the partial derivative of the above equation that:

$$\frac{\partial L}{\partial \mu_{kj}} = mq_{j}\mu_{kj}^{m-l} \left\| \boldsymbol{s}_{j} - \boldsymbol{v}_{k} \right\|^{2} - \boldsymbol{\lambda}_{j} \tag{8}$$

If the result is 0, then:

$$mq_{j}\mu_{kj}^{m-1}||s_{j}-v_{k}||^{2} = \lambda_{j}$$
(9)

$$\mu_{kj} = \left[\frac{\lambda_{j}}{\|\mathbf{s}_{j} - \mathbf{v}_{k}\|^{2} m q_{j}} \right]^{\frac{1}{m-1}}$$
(10)

It can be obtained by substituting the above equation into constraint

$$\begin{split} \sum_{i=1}^{c} \mu_{ij} &= 1 \\ \lambda_{j} &= \frac{mq_{i}}{\left(\sum_{i=1}^{c} \left\| s_{j} - v_{i} \right\|^{-\frac{2}{m-1}} \right)^{m-1}} \end{split}$$
 (11)

At this stage, the other aspects of knowledge are used to analyze and study the effect and rationality of the aggregation results of the algorithm to determine the stability, reliability, and accuracy of the clustering algorithm.

2.3 The process of K-means algorithm

The K-means algorithm first randomly selects k data objects as the initial clustering center. Then, it calculates the distance of each data object to each clustering center and classifies the data object into the class of the clustering center closest to it [9]. Next, the algorithm recalculates the new clustering center for the class. If there are no changes in the adjacent two clustering centers, the data object adjustment ends, and the clustering criterion has converged [10]. The workflow of the algorithm is shown in

- (1) A total of k objects are arbitrarily selected out of n data objects as the initial clustering centers;
- (2) The distance from each remaining data object to each clustering center

is calculated, and each data object is merged into the closest cluster;

$$C_i = \frac{1}{n_j} \sum_{i=1}^{n_j} x_i^{(j)}, \quad (j = 1, 2, ..., k)$$
is used to recalculate the

clustering center of each cluster and the value of criterion function;

(4) The reassignment of the data object: Assuming that the data object x is in cluster n, while wi and wi are the clustering centers of cluster m and

cluster n, respectively; if $\left\|x-w_i\right\|^2>\left\|x-w_j\right\|^2$ is satisfied, the data object sample x will be assigned to class m, and the value of criteria function J_b is then calculated;

(5) If $\left|J_a - J_b\right| < \varepsilon$, the calculation will terminate; otherwise, c=c+1, and steps (3)(4)(5) are repeated.

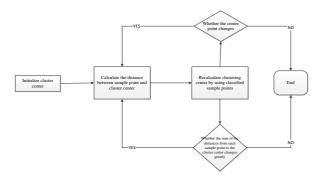


Figure 1: The workflow of K-means algorithm

Feature selection and refinement: feature selection is to select typical features from a series of candidate sets to improve the efficiency of clustering analysis. At the same time, noise and isolated point data are excluded as much as possible, the redundant and uncorrelated features are removed, and the original data is converted to another feature space so that the corresponding feature attributes can be selected. In addition, data objects should be standardized if needed. Selection of clustering algorithm: it is a critical step of clustering. Each clustering algorithm has its best application domain. For different occasions, a clustering algorithm must be selected to obtain the best clustering effect. For example, from a general and simple point of view, the K-Means clustering algorithm and the hierarchical clustering algorithm are suitable.

2.4 Deep learning K-means clustering algorithm in ballreceiving joints

This study mainly uses the deep learning K-means clustering feature analysis algorithm to study the displacements and angles of the joints while receiving the balls in football:

(1) The knee joint displacement while receiving the bounce ball with the medial side of foot: after calculation by the algorithm, the displacement range in the initial selection step is 870±200 mm, the displacement range of the support link while receiving the ball is -840±220 mm, the displacement range of the contact link is 550±180 mm, and the follow-up displacement range after receiving the ball is 124±48 mm.

The angle range of the knee joint in the selection link is 137°±9°, the angle range of the support link while receiving the ball is 93°±1°, the angle range of the contact link is 162°±6°, and the angle range of follow-up after receiving the ball is 147°±4°.

(2) The knee joint displacement while receiving the ball in the air with the medial side of foot: after calculation by the algorithm, the displacement range in the initial selection step is 243±87 mm, the displacement range of the support link while receiving the ball is 252±91 mm, the displacement range of the contact link is 306±91 mm, and the follow-up displacement after receiving the ball is -292±57 mm.

The angle range of the knee joint in the selection link is 123°±9°, the angle range of the support link while receiving the ball is 96°±5°, the angle range of the contact link is 88°±8°, and the angle range of follow-up after receiving the ball is 135°±7°.

(3) The knee joint displacement while receiving the ball in the air with the backside of foot: after calculation by the algorithm, the displacement range in the initial selection step is -260 \pm 120 mm, the displacement range of the support link while receiving the ball is 315 \pm 59 mm, the displacement range of the contact link is 376 \pm 66 mm, and the follow-up displacement range after receiving the ball is -306 \pm 116 mm.

The angle range of the knee joint in the selection link is $121^{\circ}\pm9^{\circ}$, the angle range of the support link while receiving the ball is $963^{\circ}\pm1^{\circ}$, the angle range of the contact link is $111^{\circ}\pm10^{\circ}$, and the angle range of follow-up after receiving the ball is $169^{\circ}\pm6^{\circ}$.

3. RESULTS AND DISCUSSION

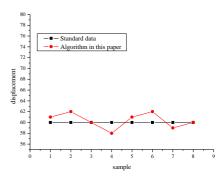


Figure 2: Knee joint displacement while receiving the ball in the air with the medial side of the foot

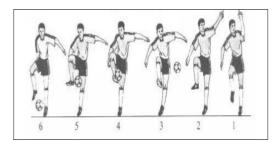


Figure 3: Biological images while receiving the ball in the air with the medial side of the foot

The displacement and biological images of the knee joint while receiving the ball in the air with the medial side of the foot are shown in Figure 2 and Figure 3, respectively. As shown in Figure 2, the displacement data of the ball received in the Z-axis direction in many sets of experiments based on the algorithm simulation of this study are very close to the standard data. It fully shows that the K-means clustering algorithm based on the deep learning in this study makes an accurate judgment of the football receiving point in the receiving process of football. The result is ideal, which can prove that the algorithm used in this study is reliable in judging the receiving point of football. As shown in Figure 3, the biological images while receiving the ball in the air with the medial side of the foot, the entire receiving process is divided into 6 steps: the preparation, raising the foot, receiving the ball, unloading the power, trapping the ball, and retracting the foot. The correct completion of these steps can realize receiving the ball in the air with the medial side of the foot.

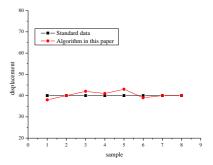


Figure 4: Knee joint displacement while receiving the bouncing ball with the medial side of the foot

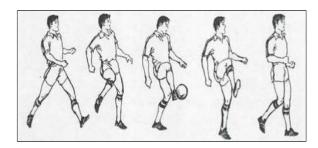


Figure 5: Biological images while receiving the bouncing ball with the medial side of the foot

The knee joint displacement while receiving the bouncing ball with the medial side of the foot is shown in Figure 4. The biological image analysis while receiving the bouncing ball with the medial side of the foot is shown in Figure 5. As shown in Figure 4, the simulation results of ball trapping by the K-means clustering algorithm are very close to the standard ball trapping data when the simulated ball trapping is performed on 8 groups of experiments. From the 1st set to the 8th group, data in 7 groups out of 8 are very close to the real values, while only 1 group of data is slightly biased. Based on such data analysis, the accuracy of the algorithm can judge the receiving points. It can be seen that the K-means clustering algorithm has a relatively significant role in judging the receiving parts of football. As shown in Figure 5, the biological images while receiving the bouncing ball with the medial side of the foot, the entire receiving process is divided into 5 steps: the preparation, raising the foot, receiving the ball, unloading the power, and trapping the ball. The correct completion of these steps can realize receiving the bouncing ball with the medial side of

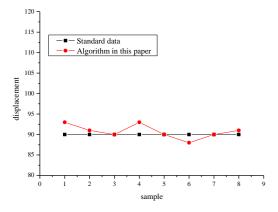


Figure 6: Hip joint displacements while receiving the ball in the air with the backside of the foot

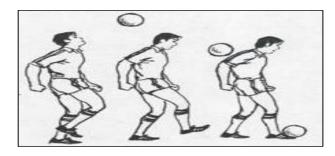


Figure 7: Biological images while receiving the ball in the air with the backside of the foot

The hip joint displacement while receiving the ball in the air with the backside of the foot is shown in Figure 6. The analysis of biological images while receiving the ball in the air with the backside of the foot is shown in Figure 7. As shown in Figure 6, the displacement data of the ball received in the Z-axis direction in 5 groups of experiments based on the K-means algorithm simulation of this study are very close to the standard data. Therefore, the advantage of the K-means algorithm in accuracy is apparent, which has proved that the K-means clustering algorithm can meet the actual needs of judging the receiving parts in football. As shown

in Figure 7, the biological images while receiving the ball in the air with the backside of the foot, the entire receiving process is divided into 3 steps: raising the foot, receiving the ball, and unloading the power. The correct completion of these steps can realize receiving the ball in the air with the backside of the foot.

4. CONCLUSION

In this study, a deep learning K-means clustering feature analysis algorithm is applied to explore the joint changes in the receiving parts of football players under different situations. The results show that while receiving the bouncing ball with the medial side of the foot, the knee joint displacement range of follow-up link after receiving the ball is 124 ± 48 mm, and the angle range is $147^{\circ}\pm4^{\circ}$. While receiving the ball in the air with the medial side of the foot, the knee joint displacement range of the follow-up link after receiving the ball is -292 ± 57 mm, and the angle range is $135^{\circ}\pm7^{\circ}$. While receiving the ball in the air with the backside of the foot. the knee joint displacement range is -306 ± 116 mm, and the angle range of the follow-up link after receiving the ball is $169^{\circ}\pm6^{\circ}$. The algorithm proposed in this study has a prominent performance in analyzing the displacement and angle changes of multiple joints at the receiving parts, which meets the actual requirements of football.

Therefore, in this study, the deep learning algorithm is used to investigate the displacements and angles of joints under three different receiving situations in football. The results show that the deep learning algorithm is accurate in determining and analyzing the data of joint variations of the receiver. The proposed algorithm in this study can provide a valuable reference for football training and promotion. However, this study is subjected to certain limitations. For example, the analysis of the receiving parts of football in actual situations is relatively complicated, involving multiple factors. While analyzing the algorithm, some factors are idealized to reduce the possible interferences. Therefore, the results obtained are slightly less convincing. The subsequent research should be more in-depth and detailed; therefore, the obtained results will be more comprehensive, which will reduce the interferences brought by other factors. The research in this study has essential reference value for future research.

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