Research Article

Basketball Motion Posture Recognition Based on Recurrent Deep Learning Model

FeiPeng Liu¹ and Wei Zhang ²

¹Changsha Medical University, Changsha 410219, Hunan, China
²Zhengzhou University, Zhengzhou 450000, Henan, China

Correspondence should be addressed to Wei Zhang; zhangwei0909@zzu.edu.cn

Received 28 March 2022; Revised 19 April 2022; Accepted 25 April 2022; Published 16 May 2022

Copyright © 2022 FeiPeng Liu and Wei Zhang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the training effect of athletes and effectively identify the movement posture of basketball players, we propose a basketball motion posture recognition method based on recurrent deep learning. A one-dimensional convolution layer is added to the neural network structure of the deep recurrent Q network (DRQN) to extract the athlete pose feature data before the long short-term memory (LSTM) layer. The acceleration and angular velocity data of athletes are collected by inertial sensors, and the multi-dimensional motion posture features are extracted from the time domain and frequency domain, respectively, and the posture recognition of basketball is realized by DRQN. Finally, the new reinforcement learning algorithm is trained and tested in a time-series-related environment. The experimental results show that the method can effectively recognize the basketball motion posture, and the average accuracy of posture recognition reaches 99.3%.

1. Introduction

In the process of basketball training and competition, coaches need to formulate corresponding training plans according to the individual conditions of different players to improve the players’ basketball skills. The traditional training method is that coaches formulate training plans based on their own training theory and training experience, combined with the skill level of basketball players [1]. This training mode is highly subjective, and coaches need to spend a lot of time analyzing the posture of athletes, and it is difficult to objectively evaluate the training effect of athletes [2]. The core of modern physical training is precision and efficiency. If the coach can accurately control the movement posture of the athlete, the training effect can be greatly improved. Therefore, collecting and analyzing the posture data of basketball players and accurately identifying the movement posture has significant significance for improving the scientificity of the coaches’ training plan and improving the training effect of the athletes, which is a new research direction [3].

With the rapid development of computer computing power, it has become possible to introduce deep learning into reinforcement learning to solve continuous state space problems. In 2015, the deep Q-network (DQN) proposed by Mnih and colleagues solved the instability problem by employing experience replay and target network techniques, reaching the level of human players on more than 2,600 Atari games, bringing depth. Since then, various improvements to DQN have emerged. Reference [4] proposes priority experience replay, which allows important experience to be used more frequently, thereby improving the efficiency of reinforcement learning. The deep double-Q network proposed by [5] in 2016 solves the problem of overestimation. In the same year, literature [6] added a competitive structure to DQN, which improved the learning efficiency of DQN. This DQN with a competitive structure is called a competitive deep Q-network [7].

DQN and its derived reinforcement learning algorithms have already been regarded as powerful algorithms, and in many areas, such as simple 2D games, the performance is
beyond the level of ordinary people. However, this excellent performance often only stays in the environment of artificially specified rules, such as most chess and games and other fields. DQN still has problems that are difficult to implement in real-world problems. This is owing to in the past research on reinforcement learning algorithms, we usually default to the state of the environment that we can fully obtain. But in the real world, we obviously don’t have the God’s perspective like in chess and games, and our acquisition of the state of the environment is obtained through observation. However, there will inevitably be information errors or even loss in observation, which makes it impossible to obtain a complete state through observation. At this time, the performance of the DQN based on the Markov decision process will naturally be greatly affected.

In order to solve the above problems, reference [8] proposed a deep recurrent Q network (DRQN), and on the basis of DQN, the first fully connected layer was changed to a long short-term memory (LSTM) layer of the same size, which solved the problem of reality environmental part observation problem. To solve the contradiction between reinforcement learning and feedback neural network parameter update, Matthew Hausknecht et al. proposed two matching parameter update methods: sequential bootstrap update and random bootstrap update. In the partially observed Markov environment, DRQN has a significant improvement over DQN.

Basketball motion posture recognition is a kind of human gesture recognition. At present, the methods of human posture recognition mainly include two categories: posture recognition based on inertial sensors and posture recognition based on image acquisition. Posture recognition based on image acquisition can be divided into monocular video recognition and multi-eye video recognition according to the number of image acquisition devices. The general idea of image capture gesture recognition is to first use the camera to capture the image or video of the athlete, and then extract the motion features hidden in the image and video. Finally, a classifier is designed to recognize the sports posture of athletes [9–13]. The image acquisition posture recognition technology has a relatively high maturity, and the accuracy of posture recognition is also very high. However, the defects of this type of method are that there are dead spots in video surveillance, a large amount of equipment, and a heavy data processing burden, which is not conducive to popularization and application [14]. The basic idea of inertial sensor recognition is that the athlete wears a simple and lightweight data acquisition sensor, sends the collected data to the processing terminal in real time, and recognizes the athlete’s posture according to various posture data [15]. This kind of method can make up for the shortcomings of image acquisition and recognition, has low requirements on the use environment and high recognition efficiency, and has become a hot method in basketball posture recognition research.

Based on these studies, we propose a basketball motion posture recognition method based on inertial sensors and DRQN. First, a data acquisition module of basketball motion posture based on inertial sensor is designed, and the features for basketball motion posture recognition are extracted from time domain and frequency domain, respectively. Then, we build a posture recognition model for basketball players based on one-dimensional convolutional layers and DRQN. Finally, we conduct experiments and evaluations on the model, and the experimental results verify the effectiveness and accuracy of the method.

2. Background

2.1. Deep Recurrent Q Network. In a real environment, it is often difficult for an agent to obtain a complete state. In other words, real-world environments usually do not strictly conform to Markov properties [8]. Partially Observable Markov Decision Processes (POMDPs) mathematically model the connection between observations and the true state. Therefore, it can better describe the dynamics of the real environment [16]. POMDP introduces observation space Ω and conditional observation probability function O on the basis of Markov decision process (MDP), and defines the agent’s primary perception of the environment as observation o ∈ Ω. There is a certain connection between the observation and the real state, and this connection is described by probability, that is, o ∼ Ω (s). In this way, the POMDP can be described by six parameters (S, A, P, R, Ω, O), which represent the state space, action space, state transition probability function, reward function, and the newly added observation space Ω relative to MDP, and the conditional observation probability function O. Obviously, when the observation o corresponds to the state s one-to-one, the POMDP becomes the MDP. The DRQN proposed by Matthew Hausknecht and Peter Stone in 2017 modified the network structure of DQN by changing its first fully connected layer to an LSTM layer of the same size. Because of the introduction of memory capabilities, neural networks are better able to combat incomplete information due to observations. The neural network structure of DRQN is shown in Figure 1.

2.2. Input and Output Structure. The hardware structure of data acquisition is shown in Figure 2. The functions of the hardware part include data acquisition and data transmission, including four data acquisition nodes and one data transmission base station. The data acquisition node consists of a three-axis gyroscope MPU3050 three-axis accelerometer and a magnetometer LSM303DLH, which, respectively, collect the angular velocity and acceleration data of the human body. The core component of the data sending base station is the wireless transceiver nRF24L01, which receives the data collected by the node and sends the data to the data terminal through the wireless network. The core processing function of the data acquisition module is completed by the 32-bit ARM microcontroller STM32F103. The energy supply of the data acquisition module is responsible for a 3.7 V lithium-ion battery.

The signal transmission of the entire data acquisition module includes two parts: First, the sensor node sends the collected human body posture data to the data transmission base station. The second is that the data transmission base
station sends data to the signal transmission between the processing terminal sensor node and the data transmission base station, which is realized based on the wireless sensor network. The problem that needs to be overcome is to reduce the data collision rate, reduce data loss, and improve the accuracy of data collection. The signal transmission between the data transmission base station and the processing terminal is realized based on the star topology network, and the time division multiplexing protocol is adopted. The problem that needs attention is to calibrate the clock deviation between different nodes and keep the time uniform.

In data collection, multiple sensor nodes are generally used to collect relevant information. In addition to the structure of the node itself, the effective and complete transmission of data is another major problem. At present, according to different data transmission media, data transmission forms are mainly wired and wireless. The wired transmission mode is more stable and reliable, but it has not been widely used because of its complex installation and wiring and many restrictions on motion detection. There are many advantages in the field of human body posture recognition; often using wireless communication technology has Bluetooth, Zig Bee, wireless radio frequency identification, wireless transmission mode can reduce the influence of the sensors on the normal activity, so most systems adopt the form of wired transmission. In the design of wireless transfer protocol, it forms the network architecture. Among the common network topology, star topology and mesh topology are widely used in practical applications. In the application of body area network, star topology requires multiple nodes to be directly connected to the receiving node, so it is often used because of its simple communication structure and convenient implementation.

Compared with star topology structure, network topology structure is more complex, but it can be used in a multiple way to reduce the path loss caused by diffusion, and the data transmission is only between adjacent nodes, can envos point to keep the smaller energy transmission network protocol setting need according to their own research needs in setting reasonable network structure.

3. The Proposed Model

3.1. Feature Extraction of Basketball Motion Posture. The basketball player posture acquisition data that mainly includes acceleration information and angular velocity information, respectively, uses \( a_x^n, a_y^n, a_z^n \) to represent the acceleration of the \( x, y, z \) axes of the \( n \)-th sampling point. \( g_x^n, g_y^n, g_z^n \) represent the angular velocity of the \( x, y, z \) axes of the \( n \)-th sampling point. The vector sum of the acceleration at the \( n \)-th point is

\[
a_n = \sqrt{(a_x^n)^2 + (a_y^n)^2 + (a_z^n)^2}.
\]  

Similarly, the vector sum of the angular velocity at the \( n \)-th point is

\[
g_n = \sqrt{(g_x^n)^2 + (g_y^n)^2 + (g_z^n)^2}.
\]  

Combine the three acceleration vectors, three angular velocity vectors input by the data acquisition module, and the vector sum of the acceleration and angular velocity calculated by equations (1) and (2) into an eight-dimensional feature matrix. If a total of \( N \) samples are collected point, each sample is an \( N \times 8 \) feature matrix. The time-domain features of basketball player posture recognition are mean and variance, and the mean of each point is

\[
\mu_n = \frac{1}{N} \sum_{n=1}^{N} a_n.
\]  

The variance of each sampling point is

\[
\sigma^2 = \frac{1}{N} \sum_{n=1}^{N} (a_n - \mu_n)^2.
\]  

The extracted time-domain features include four dimensions of the acceleration sensor \( x, y, \text{ and } z \) axis and the
mean value of the acceleration vector sum; four dimensions of the angular velocity sensor \( x, y, \) and \( z \) axis and the mean value of the angular velocity vector sum; four dimensions of the acceleration sensor \( x, y, \) and \( z \) axis and the variance of the acceleration vector sum and the angular velocity sensor. The variance of the \( x, y, \) and \( z \) axis and the angular velocity vector sum has a total of four dimensions, and a total of 16-dimensions of time-domain attitude parameters.

Next, based on the Fourier transform principle, the time-domain acquisition data is transformed into the frequency domain, and the formula is

\[
S(n) = \sum_{n=1}^{N-1} a_n e^{-i(2\pi n N)} ,
\]

where \( S(n) \) represents the \( n \)th adoption point value in the frequency domain. The frequency-domain feature for basketball player posture recognition is the peak value of the Fourier transform, that is,

\[
f = \frac{K f_s}{N} ,
\]

where \( K \) is the number of sampling points in the frequency domain and \( f \) is the frequency used by the data acquisition sensor.

The extracted frequency-domain features include the frequency-domain peak value of the acceleration sensor \( x, y, \) and \( z \) axis and the six-dimensional frequency value corresponding to the peak value, the acceleration vector and the two-dimensional frequency value corresponding to the frequency-domain peak value and peak value, and the angular velocity sensor. The frequency-domain peak value of the \( x, y, \) and \( z \) axis and the corresponding frequency value of the peak value are six dimensional. The angular velocity vector and the frequency-domain peak value and peak value corresponding to the frequency value are two dimensional, with a total of 16-dimensional features.

3.2. Model Establishment. Feature selection is a variable selection method, also known as attribute selection or variable subset selection, which is a process of selecting a subset of relevant attributes in order to build a classification model. The primary reason for feature selection is that in the feature set obtained by feature extraction, not all attributes are relevant and useful, and the selection of some attributes may be redundant. The introduction of those irrelevant attributes not only has no effect on the construction of the model, but also makes the constructed model more complex due to the redundancy and irrelevance of the data. Therefore, it is extremely necessary to conduct reasonable feature screening. There is a big difference between feature selection and feature extraction. The purpose of feature extraction is to extract feature vectors from the original data, while feature selection is to select a suitable subset of feature vectors from these feature vectors. There are three main purposes of feature selection: (1) simplify the model and reduce the computational complexity; (2) shorten the training time; and (3) strengthen the promotion to avoid the problem of overfitting. Commonly used feature selection algorithms are generally obtained by combining evaluation functions with algorithms such as sequential forward/forward search, decision tree, best-first search, and genetic algorithm. Among them, the evaluation algorithm is a function that can reflect the pros and cons of the selected feature subset, and can be used to solve the correlation between features and classification, classifier error rate, etc. In addition, the commonly used methods for feature selection to reduce the feature dimension and reduce the amount of system computation are: linear discriminant analysis (LDA), principal component analysis (PCA), and other algorithms [17].

The recognition of basketball motion posture is to construct a classifier that can recognize the athlete’s posture according to the features of the data collected by the sensor. The extracted pose features are input into the classification, and the classifier outputs a specific basketball action. After feature extraction, a 16-dimensional feature parameter set for identifying the posture of basketball players is obtained. However, some of these feature parameters are features that are not related to the basketball player’s posture, or have low correlation. There are also some features that represent redundant information. If these features are input into the classifier at the same time, it will not only reduce the recognition performance of the classifier, but also seriously affect the recognition efficiency of the classifier. Therefore, it is necessary to select features before performing basketball pose recognition. The purpose of feature selection is to reduce dimensionality in the data. At the same time, the feature parameters that are highly relevant to the posture recognition of basketball players are screened out. After experimental testing, the PCA method was selected to realize the selection of characteristic parameters.

In the 16-dimensional feature, the optimal feature is selected based on the PCA method. Next, the classifier is constructed to recognize the posture of the basketball player. Both DQN and DRQN neural networks contain two-dimensional convolutional layers. Typically, if the input is not an image, but just a feature vector, the neural network used by DQN and DRQN will not contain convolutional layers. However, the feature extraction capability of convolutional layers can be applied not only to extract image features, but also to extract features in the temporal dimension [18]. Therefore, this model utilizes the temporal dimension feature extraction capability of a 1-dimensional convolutional layer to extract temporal features of athlete poses.

The network structure of the proposed model is shown in Figure 3. On the basis of the neural network used in DRQN, a one-dimensional convolutional layer is added, which is called a one-dimensional convolutional recurrent neural network. The one-dimensional convolutional layer will convolve the input data in the time dimension and extract its features in the time dimension. Experiments show that this can improve the feature extraction ability and fitting ability of the neural network, thereby improving the decision-making level of the agent, and making the agent perform better in the environment related to time series.
3.3. The Recognition of Basketball Motion Postures. To solve the convergence problem of deep reinforcement learning in the environment with large state-space dimension, this study uses a one-dimensional convolutional layer to extract the features of the state in the time dimension. Let the input be $X \in \mathbb{R}^{N \times C \times L_{in}}$ and the output be $Y \in \mathbb{R}^{N \times C_{out} \times L_{out}}$, then the mathematical expression of the one-dimensional convolutional layer is

$$ Y[i, j, :] = \beta[j] + \sum_{k=0}^{c_{in}-1} \alpha[j, k, :] \otimes Y[i, k, :]. \quad (7) $$

In (7), the symbol $\otimes$ is the cross-correlation operation. $N$ is the size of a batch of training data. $C_{in}$ and $C_{out}$ are the number of channels of input and output data, respectively. $L_{in}$ and $L_{out}$ are the lengths of input and output data, respectively. A kernel size represents the one-dimensional convolution kernel size. $\alpha \in \mathbb{R}^{C_{out} \times C_{in} \times \text{kernel size}}$ is the one-dimensional convolution kernel of this layer. $\beta \in \mathbb{R}^{C_{out}}$ is the bias term of this layer.

The LSTM layer is a recurrent neural network that brings memory capabilities to the neural network. Generally, the input of the LSTM layer is a time series $x$ of a certain feature vector $x \in \mathbb{R}^{N \times L_{in} \times H_{in}}$. For simplicity, assume that a batch contains only one piece of data and the feature vector contains only one feature, that is, $x \in \mathbb{R}^{L_{in}}$. It can be seen that $x = [x_1, x_2, \ldots, x_t, \ldots, x_{L_{in}}]^T$, then for the element $x_i$ at any time in $x$, the mathematical expression of the LSTM layer is

$$ \begin{align*}
    i_t &= \sigma(W_{ix}x_t + b_i + W_{hi}h_{t-1} + b_h), \\
    f_t &= \sigma(W_{xf}x_t + b_f + W_{hf}h_{t-1} + b_h), \\
    g_t &= \tanh(W_{xg}x_t + b_g + W_{hg}h_{t-1} + b_h), \\
    o_t &= \sigma(W_{xo}x_t + b_o + W_{ho}h_{t-1} + b_h), \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g_t, \\
    h_t &= o_t \odot c_t.
\end{align*} \quad (8) $$

In (8), the symbol $\odot$ represents the Hadamard product. $N$ is the size of a batch of training data. $L_{in}$ is the length of the time series in the time dimension. $H_{in}$ is the feature number included by the time series. $i_t$, $f_t$, $g_t$, and $o_t$ are called input
gates, forget gates, cell gates, and output gates at time $t$, respectively. $c_t$ and $h_t$ are called time $t$, which denote cell states and hidden states, respectively.

The fully connected layer is the most classic component of the neural network. According to the classical form, let the input of the fully connected layer be the feature vector $X \in \mathbb{R}^{N \times H_{in}}$ and the output be $Y \in \mathbb{R}^{N \times H_{out}}$, then the mathematical expression of the fully connected layer is

$$Y[i,:] = \sigma(X[i,:]A + b),$$

where $\sigma$ is a nonlinear activation function, commonly used are sigmoid function and ReLU function. $N$ is the size of a batch of training data. $H_{in}$ and $H_{out}$ are the number of features of the input and output data, respectively. $A$ is the weight of the layer, and $b$ is the bias term of the layer. As seen in Figure 4, the detail neural network structure framework of our scheme is given.

4. Experimental Results and Evaluation

In the experimental process, a total of 100 basketball players were collected in four postures: shooting, passing, dribbling, and catching. About 100 sets of data were collected for each posture, and 40,000 sample data were obtained. These data were iterated 100 times in the above model. In the process of collecting basketball motion posture data, the testers completed the prescribed basketball movements according to the preset posture and according to their usual exercise habits. According to the characteristics of the body movements of the athletes, a classifier is constructed to identify the posture of the basketball players. Four classical classifier, that is, random forest, support vector machine, SOM neural network, and Bayesian network, as a comparison with our model, is verified with the validation set of basketball motion pose. The comparison of experimental results is shown in Table 1.

The experimental results show that for the recognition of basketball poses, our model has the highest average recognition accuracy, reaching 99.3%. Among other models, the SVM algorithm has the highest recognition accuracy, with an average recognition accuracy of 97.1%. The average recognition accuracies of SOM neural network, Bayesian network, and random forest are 91.5%, 90.8%, and 89.4%, respectively. This result verifies the accuracy of the proposed basketball motion recognition method based on multi-feature fusion and DRQN. This is because compared with these traditional machine learning algorithms, DRQN has a deeper network structure and extract more in-depth features of basketball poses, thereby improving the accuracy of recognition.

Figure 5 shows the distribution of the output results of the model after the first epoch and the 100-th epoch. The red dots are the characteristic distribution of the samples, and

| Postures     | Random forest/% | Support vector machine/% | SOM neural network/% | Bayesian network/% | Our model/% |
|--------------|-----------------|--------------------------|---------------------|-------------------|------------|
| Shooting     | 87.9            | 96.9                     | 93.2                | 93.9              | 98.9       |
| Passing      | 86.3            | 98.3                     | 94.1                | 89.1              | 99.6       |
| Dribbling    | 90.2            | 97.1                     | 95.8                | 90.7              | 99.2       |
| Catching     | 93.2            | 96.2                     | 94.2                | 92.2              | 99.5       |
| Average      | 89.4            | 97.1                     | 94.3                | 91.4              | 99.3       |

Figure 5: The training results of our model.
the blue dots are the characteristic distribution of the model results. It can be seen that after the 100-th epoch, the training results are more in line with the feature distribution of the original data than the first epoch.

5. Conclusion

In recent years, with the development of wireless sensor networks, and microelectronics equipment technology, the human body gesture recognition has attracted extensive attention in various fields, such as health sports game movie. Based on posture recognition based on the human body, posture recognition of the movement of athletes in the field of basketball was studied and analysis.

In this study, the problem of basketball pose recognition is studied, and a new basketball posture recognition method based on DRQN is proposed. Inertial sensors are used to collect athletes’ posture data. After the features are extracted, PCA is used to reduce the dimensionality of the features. The introduction of the LSTM layer enables our model to have a certain memory capacity. The addition of a one-dimensional convolutional layer gives our model a stronger feature extraction ability on the basis of its memory ability, and then it can process information in the time dimension more efficiently. At the same time, the one-dimensional convolutional layer also increases the fitting ability and stability of the neural network, making the training process of deep reinforcement learning more stable. After 100-th epoch, the accuracy of recognizing basketball poses is significantly improved. Compared with other methods for recognizing basketball motion posture, our model has better performance.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

Acknowledgments

The work was not supported by any funding.

References

[1] W.-F. Wang, C.-Y. Yang, and D.-Y. Wang, “Analysis of movement effectiveness in badminton strokes with accelerometers,” Genetic and Evolutionary Computing, pp. 95–104, Springer, Berlin, Germany, 2016.
[2] F. Dadashi, A. Arami, F. Crettenand et al., “A hidden Markov model of the breaststroke swimming temporal phases using wearable inertial measurement units,” in Proceedings of the Body Sensor Networks (BSN), pp. 1–6, Cambridge, MA, USA, May 2013.
[3] L. A. Schwarz, A. Bigdelou, and N. Navab, “Learning Gestures for Customizable Human-Computer Interaction in the Operating Room,” Med Image Comput Comput Assist Interv, vol. 14, 2011.
[4] T. Schaul, J. Quan, I. Antonoglou, and D. Silver, “Prioritized Experience Replay,” in Proceedings of the ICLR, San Juan, Puerto Rico, May 2016.
[5] H. V. Hasselt, A. Guz, and D. Silver, “Deep Reinforcement Learning with Double Q-learning,” in Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, Phoenix, Arizona, February 2015.
[6] Z. Wangz, M. Hessel, T. Schaul, and L. Marc, “Dueling Network Architectures for Deep Reinforcement Learning,” in Proceedings of the International Conference on Machine Learning, PMLR, pp. 1995–2003, London, UK, June 2016.
[7] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, and D. Hassabis, “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.
[8] M. Hausknecht and P. Stone, “Deep Recurrent Q-Learning for Partially Observable MDPs,” 2015, https://arxiv.org/abs/1507.06527.
[9] Y. L. Hsu, J. S. Wang, Y. C. Lin et al., “A Wearable Inertial-Sensing-Based Body Sensor Network for Shoulder Range of Motion assessment,” in Proceedings of the 2013 International Conference on Orange Technologies (ICOT), March 2013.
[10] S. Asai, K. Watanabe, and Y. Kurihara, “Measurement and Analysis of Running Form Using 3-D Acceleration and Gyroscopic sensor,” in Proceedings of the SICE Annual Conference (SICE), IEEE, Akita, Japan, August 2012.
[11] B. Longstaff, S. Reddy, and D. Estrin, “Improving Activity Classification for Health Applications on mobile Devices Using Active and Semi-supervised learning,” in Proceedings of the Pervasive Computing Technologies for Healthcare International Conference, Munich, Germany, March 2006.
[12] L. Oudre, M. Diron, and C. Simon, “Segmentation and classification of dynamic activities from accelerometer signals,” Journal of Innovation Impact, vol. 6, 2013.
[13] Y. Wang, “Real-time collection method of athletes’ abnormal training data based on machine learning,” Mobile Information Systems, vol. 2021, Article ID 9938605, 11 pages, 2021.
[14] G. M. Paul, B. P. David, and L. M. Clare, “The physical and physiological demands of basketball training and competition,” International Journal of Sports Physiology and Performance, vol. 5, no. 1, pp. 75–86, 2010.
[15] A. D. Ignatov and V. V. Strijov, “Human activity recognition using quasiperiodic time series collected from a single tri-axial accelerometer,” Multimedia Tools and Applications, vol. 75, no. 12, pp. 7257–7270, 2016.
[16] M. Spaan, “Fuzzy Reinforcement Learning Control for Decentralized Partially Observable Markov Decision processes,” in Proceedings of the IEEE International Conference on Fuzzy Systems, June 2011.
[17] N. Y. Ke and R. Sukthankar, “PCA-SIFT: A More Distinctive Representation for Local Image descriptors,” in Proceedings of the IEEE Computer Society Conference on Computer Vision & Pattern Recognition, June 2004.
[18] S. Albawi, T. A. Mohammed, and S. Alzawi, “Understanding of a Convolutional Neural Network,” in Proceedings of the International Conference on Engineering and Technology, Antalya, Turkey, August 2017.