Abstract—Action recognition has attracted increasing attention from RGB input in computer vision partially due to potential applications on somatic simulation and statistics of sport such as tennis game. Recently, deep learning based methods have achieved promising performance for action recognition. In this paper, we proposed a historical Long Short-Term Memory adopted with convolutional neural network representations for three dimensional tennis shots recognition. First, the local two-dimensional convolutional neural network spatial representations were extracted from each video frame individually using a pre-trained convolutional neural network. Then, a historical Long Short-Term Memory model was proposed to take the output state at time t and the historical updated feature at time t-1 to generate a holistic feature vector using a score weighting scheme. Finally, we used the adopted CNN and deep historical LSTM to map the original visual sequences of tennis action into a spatial-temporal semantical description and classified the action video. Experiments on the benchmarks demonstrate that our method which used only simple raw RGB video can achieve better performance than the state-of-the-art baselines for tennis shot recognition.

Index Terms—tennis game, action recognition, deep learning, Long Short-Term Memory, convolutional neural networks.

I. INTRODUCTION

Due to the great increasing of sport game videos, it is implementable to analysis the technology and movement of players using the collected video data. Such as [1] tries to evaluate a basketball player’s performance from his/her first-person video. Many works have been devoted in vision-based sport action recognition in recent years [2], [3]. Several public video datasets such as UCF-Sport [3] and Sports-1M [4] are provided for this problem. Tennis has received widely attention from the all the world. However, since lack of data, there are few literatures analyzing tennis actions. This paper focuses on automatically recognizing different tennis actions using the RGB videos. Zhu et al. [5], [6] used the support vector machine to classify tennis videos into left-swing and right-swing actions by optical flow based descriptor. Farajidavar et al. [7] employed the transfer learning to classify tennis videos into non-hit, hit and serve actions. However, they have just analyzed a few actions for playing tennis. Luckily, Gourgari et al. [8] have presented a tennis actions database called THETIS dataset. It consists of 12 fine-grained tennis shots acted by 55 different subjects multiple times at different scenes with dynamic background. The objective of analyzing the THETIS dataset is to classify the videos into the 12 pre-defined tennis actions from raw video data. Based on this database, Mora et al. [2] have proposed a deep learning model for domain-specific tennis action recognition using RGB video content. They tried to use long-short term memory networks (LSTMs) to describe each action, since LSTMs can remember information for long periods of time.

Recently, deep learning based methods have achieved promising performance for action recognition. Li et al. [9] presented a skeleton-based action recognition method using LSTM and convolutional neural network (CNN). Cheron et al. [10] proposed a pose-based convolutional neural network feature for action recognition. Gammulle et al. [11] have presented a deep fusion framework for human action recognition, which employs a convolutional neural network to extract salient spatial features and LSTMs to model temporal relationship. Zhang et al. [12] used the multi-layer LSTM networks to learn the geometric features on skeleton information for action recognition. Liu et al. [13] proposed a spatio-temporal LSTM with trust gates for 3D human action recognition. Zhu et al. [14] presented a co-occurrence skeleton feature learning based on regularized deep LSTM networks for human action recognition. Lee et al. [15] proposed an ensemble learned temporal sliding LSTM networks for skeleton-based action recognition. Tsunoda et al. [16] used the hierarchical LSTM model for football action recognition. Song et al. [17] presented a spatio-temporal attention-based LSTM networks for recognizing and detecting 3D action. Liu [18] proposed a global context-aware attention LSTM networks for 3D action recognition.

At least two important aspects influence the performance of action recognition: spatial representation and temporal modeling. Hence, in this paper, we propose a framework using convolutional neural networks with historical Long Short-Term Memory networks for tennis action recognition. First, we extract deep spatial representation for each frame by Inception [19] which is a famous convolutional neural network and pre-trained on ImageNet dataset. The most importance is that a historical Long Short-Term Memory units are proposed to modeling the temporal cues. For THETIS dataset, there are 12 fine-grained tennis shots and they are similar with each other. It’s a challenge to distinguish different tennis shots. As we know, for each action, its historical evolution as time is important. Long Short-Term Memory is widely used for sequence model. The original Long Short-Term Memory only
model the local representation of sequences. However, the global or holistic representation, such as historical information can not be described through LSTM. Therefore, we have proposed an recurrent neural network(RNN) architecture using an extra layer to describe the historical information for action recognition. Besides, for a video clip, some frames may be very critical to action recognition. However, in original Long Short-Term Memory model, we can’t automatically focus on those key frames. Therefore, we present a score weighting scheme by taking the output state at time \( t \) and the historical information at time \( t - 1 \) to generate the feature vector that describing the historical information of human action. In our framework, we can automatically pay more attention to those impressive frames and omit the insignificant clips. Additionally, the update duration of historical state may be very long so that large errors may be accumulated in the iteration process. So we proposed an error truncation technology to re-initialize the historical state at current time and drop the accumulated errors. In order to extract temporal features, we developed a five-layer deep historical Long Short-Term Memory network to learn the representation of the spatial feature sequences. In conclusion, the CNN model and the deep historical LSTM model are adopted to map the raw RGB video into a vector space to generate the spatial-temporal semantical description and classify the action video content. Experiments on the benchmarks demonstrate that our method outperforms the state-of-the-art baselines for tennis shot recognition using only raw RGB video.

The main contributions of our work are listed as follows

(1) We proposed a Long Short-Term Memory units based RNN architecture with an extra historical layer, called historical Long Short-Term Memory, to model the holistic information and build high level representation for visual sequences.

(2) In our proposed historical Long Short-Term Memory framework, a historical layer was introduced to model the historical information of hidden state. So the proposed model can learn the global and holistic feature from the original human action sequence.

(3) The proposed historical Long Short-Term Memory used a weighting scheme to enhance the influence of key frames that are important to action recognition during the updating process of historical state. So it help the pattern classifier to automatically pay more attention to the important frames and omit the insignificant clips.

(4) Due to the update duration of historical state is long and large errors may be accumulated in the update process, we proposed an error truncation technology to re-initialize the historical state at current time and drop the accumulated errors.

(5) We proposed a framework based on CNN and deep historical Long Short-Term Memory networks for tennis action recognition . Firstly ,we used the pre-trained Inception networks to build the spatial features from raw RGB frames. Then we proposed a five-layer historical Long Short-Term Memory networks for action video recognition. The sequences of spatial feature vectors were fed into this deep historical Long Short-Term Memory model to build the temporal feature of videos.

The rest of the paper is organized as follows. Section 2 describes the proposed method. Section 3 shows the experimental results and analysis. Finally, section gives the conclusion and future work of the paper.

II. Method

A. Framework

In this paper, we adopted an improved Long Short-Term Memory network accompanied by convolutional neural network for tennis action recognition. The whole framework is illustrated in Figure 1. Firstly, each frame of the original RGB video is fed to the Inception V3 model for capturing the appearance and spatial information as the local feature. This model is pre-trained on the Large Scale Visual Recognition Challenge 2012 (ILSVRC-2012) ImageNet. Then a Long Short-Term Memory model is adopted as a complement to the CNN model to capture the contextual information in the temporal domain. The spatial features extracted from Inception model are fed to the LSTM model as the input. The CNN features are suitable to feed into the LSTM model because they provides rich spatial information. Specially, we introduced an improved version of the Long Short-Term Memory, called historical Long Short-Term Memory, to describe the historical information as the global feature. It employs a score weighting scheme to generate the iterated feature vector using the output state at time \( t \) and the historical state at time \( t - 1 \). Then a five-layer deep historical LSTM network is builted. Each layer of it has 30 historical LSTM units. Finally, we use the output of deep historical LSTM networks as the spatial-temporal semantical description of visual sequences. It is fed to a soft-max layer for classifying the action video content.

B. RNN and LSTM

RNN is a powerful sequence model widely used in speech recognition and natural language processing. For a typical RNN model, the update equation at time \( t \) is described as follows.

\[
\begin{align*}
  h_t &= g(b + W h_{t-1} + U x_t) \\
  \hat{y}_t &= \text{softmax}(c + V h_t)
\end{align*}
\]

where \( h_t \) is the state of the \( t \)-th neuron, and \( x_t \) is the observation at time \( t \) which is the input of the \( t \)-th neuron. In a typical RNN model, the update state \( h_t \) of the \( t \)-th neuron is determined by the previous neuron state \( h_{t-1} \) and the input \( x_t \) of the \( t \)-th neuron. \( g(\cdot) \) is the activation function. Usually, the sigmoid function \( \sigma(\cdot) \) or hyperbolic tangent function \( \tanh(\cdot) \) can be employed as the activation function. \( \hat{y}_t \) denotes the prediction of label \( y \) at time \( t \). It is estimated by the output response \( h_t \) of state neuron at \( t \) time using a softmax function. \( U, W \) and \( V \) are the weight matrices. \( b \) and \( c \) are the bias vectors.

Traditional RNNs is suitable for modeling the short-term dynamics but unable to capture the long-terms relations. LSTM is an improved version of RNN architecture for learning long-range dependencies and resolving the ”vanishing gradient” problem. In the typical LSTM model, the \( t \)-th hidden
C. Historical LSTM

The typical LSTM use the last layer to encode the input sequence. When it is adopted for action video recognition using image sequences, the last frame of the video will have the most influence on the action class recognition result. And the previous frames have a minimal impact on the classification due to the forgetting effect. However, a human action is often defined by the whole movement process. To better describe the human action, we embed the historical information of human movement to the LSTM model for building a global feature. We propose an improved version of the Long Short-Term Memory network, called historical Long Short-Term Memory, to describe the historical information. The structure of model is illustrated in Figure 2. The historical Long Short-Term Memory network is an LSTM units based RNN architecture using an added extra layer called historical layer to describe holistic information of human movement.

In the historical Long Short-Term Memory model, a historical state \( l_t \) is introduced at time \( t \). It is generated by a score weighting scheme using the response state \( h_t \) at time \( t \) and the historical state at time \( t - 1 \). If the classification loss of historical state at time \( t - 1 \) is smaller than that of response state at time \( t \), then we generate the new historical state at time \( t \) using the weighted sum of the current response state at time \( t \) and the historical state at time \( t - 1 \). The weight of the response state or the historical state is computed according to its classification loss. Using such weighting scheme, the influence of key frames which are important to action class recognition can be enhanced during the updating process of historical state. So it help the pattern classifier to automatically pay more attention to the important frames and omit the insignificant clips. However, if the classification loss of historical state at time \( t - 1 \) is lager than that of response state at time \( t \), which means too much errors have been accumulated in the long process of the historical state iteration, then we recalculate the current historical state at time \( t \) using the response states from time \( t - \tau \) to time \( t \). Here \( \tau \) is a parameter to control the length of state sequence used to re-initialize the historical state and drop the previous historical state with large errors. It determines when to forget the previous response states if they are corresponding to large errors. The update equation of historical state \( l_t \) is expressed as follows.

\[
l_t = \begin{cases} \alpha_t h_t + (1 - \alpha_t) l_{t - 1}, & \text{if } \epsilon_{ht} \geq \epsilon_{l_{t - 1}} \\ \sum_{k=1}^t \omega^t_{hk} h_k, & \text{if } \epsilon_{ht} < \epsilon_{l_{t - 1}} \end{cases}
\]

\[
\alpha_t = \frac{\ln(\epsilon_{l_{t - 1}})}{\epsilon_{ht}}
\]

where \( \alpha_t \) is the weight controlling a balance between the response \( h_t \) and the last historical state \( l_{t - 1} \). It is calculated by the following formula:

\[
\alpha_t = \frac{1}{2} \ln\left(\frac{\epsilon_{l_{t - 1}}}{\epsilon_{ht}}\right)
\]

The typical LSTM use the last layer to encode the input sequence. When it is adopted for action video recognition using image sequences, the last frame of the video will have the most influence on the action class recognition result. And the previous frames have a minimal impact on the classification due to the forgetting effect. However, a human action is often defined by the whole movement process. To better describe the human action, we embed the historical information of human movement to the LSTM model for building a global feature. We propose an improved version of the Long Short-Term Memory network, called historical Long Short-Term Memory, to describe the historical information. The structure of model is illustrated in Figure 2. The historical Long Short-Term Memory network is an LSTM units based RNN architecture using an added extra layer called historical layer to describe holistic information of human movement.

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\[
l_t = \begin{cases} \alpha_t h_t + (1 - \alpha_t) l_{t - 1}, & \text{if } \epsilon_{ht} \geq \epsilon_{l_{t - 1}} \\ \sum_{k=1}^t \omega^t_{hk} h_k, & \text{if } \epsilon_{ht} < \epsilon_{l_{t - 1}} \end{cases}
\]

\[
\alpha_t = \frac{\ln(\epsilon_{l_{t - 1}})}{\epsilon_{ht}}
\]

where \( \alpha_t \) is the weight controlling a balance between the response \( h_t \) and the last historical state \( l_{t - 1} \). It is calculated by the following formula:

\[
\alpha_t = \frac{1}{2} \ln\left(\frac{\epsilon_{l_{t - 1}}}{\epsilon_{ht}}\right)
\]

where \( \epsilon_{ht} \) denotes the loss between the training label \( y_t \) at time \( t \) and the estimated label \( \hat{y}_t \) at time \( t \) which is produced by the softmax function on \( c + V h_t \). In this paper, the training label \( y_t \) at time \( t \) is set as the action label of the training video. \( \omega^t_{hk} \) denotes the weight of response \( h_k \). It is calculated by:
The stacked network. Each layer has 30 units. The probability
in the experiments. We use a five-layer deep historical LSTM in
D. Implementation Details

where $\tau$ is the parameter controlling the forgetting effect.
Finally, the last historical state $l_T$ are used as the output
of historical LSTM model. It describe the holistic information
of human movement history and can be used for action video
recognition. For example, a softmax layer can be employed to
provide the estimated label $\hat{y}$ based on the last historical state $l_T$:

$$\hat{y} = \text{softmax}(d + Ql_T)$$

where $d$ and $Q$ is the bias vector and weight matrix of
the softmax layer respectively.

D. Implementation Details

TensorFlow and Python are employed as the deep learning
platform. An NVIDIA GTX1080Ti GPU is adopted to run the experiments. We use a five-layer deep historical LSTM in
the stacked network. Each layer has 30 units. The probability
of dropout is set as 0.5. The initial learning rate is set as
0.001 on historical LSTM model. The learning rate is set by
exponentially decaying with a base of 0.96 every 100 000
steps during the training process. The regularization value of
of historical LSTM model is set as 0.004. The batch size fed
to the model is set as 32. The Adam Optimizer is used to
trained the network for historical LSTM model.

III. EXPERIMENTAL RESULTS
A. General action recognition

1) Dataset: We use the HMDB51 dataset [20] to show the
effectiveness of the proposed historical LSTM for general
action recognition tasks. The HMDB51 dataset is a common
used dataset including 6849 videos. It consists of 51 human
action categories including facial actions and body movement.
The original RGB videos of HMDB51 dataset are used to test
the proposed framework.

2) Results: The five-fold cross-validation strategy is used
to split the dataset to the training set and test set. We compared
the proposed historical LSTM to the typical LSTM. The parameter $\tau$ of historical LSTM is fine tuned from 2 to 5.
Table 1 shows the accuracy values of the methods. As is
shown in the table, the average accuracy in prediction of the
historical LSTM model achieves a best accuracy 0.73 when
the parameter $\tau$ is set as 2. Furthermore, the average accuracy
of the historical LSTM model is 0.62 when the parameter $\tau$
is set as 3. When the parameter $\tau$ is set as 4, the historical
LSTM model achieves an accuracy of 0.63. However, when $\tau$
is set as 5, the accuracy of historical LSTM decline to 0.62.
It is seen that setting the parameter $\tau$ to a medium number
according to the time period in the WTSM model is better.
Meanwhile, the average accuracy of the LSTM model is 0.47.
The experimental results shows that the proposed historical
LSTM model outperforms LSTM model. We also compared
the proposed model to other state-of-the-art models using RGB
data, such as Spatial stream ConvNet [21], Soft attention
model [22], Composite LSTM [1] and Mora’s model [2]. As
shown in Table 1, the correct recognition rate of our method
exceeds that of the other models using RGB data. We also
compared our model using RGB data to other methods using
different information. They are the two-stream ConvNet using
optical flow information [21], Wang’s model using Fisher
Vectors [23], and Wang’s model using a combination of HOG,
HOF and MBH [23]. The experimental results show that our
model achieves a high accuracy using the very simple RGB
data and outperform the compared models. It will results in
better results if other information such as optical flow data,
skeletons data and depth information are added to the input of
our proposed model.

B. Tennis action recognition

1) Dataset: The Three Dimensional Tennis Shots
(THETIS) dataset [8] is used for evaluating the proposed
method. This dataset contains 12 basic tennis actions each
of which are acted repeatedly by 31 amateurs and 24 expe-
rienced players. The 12 tennis actions performed by actors
are: Backhand with two hands, Backhand, Backhand slice,
Backhand volley, Forehand flat, Forehand open stands, Fore-
hand slice, Forehand volley, Service flat, Service kick, Service

Fig. 2. The structure of historical Long Short-Term Memory model

$$\omega^t_k = \begin{cases} 0, & \text{if } k \leq \tau \\ \frac{k}{1 - \tau}, & \text{if } k > \tau \end{cases}$$

where $\tau$ is the parameter controlling the forgetting effect.
slice and Smash. Each actor repeats each tennis action 3 to 4 times. There are totally 8734 videos of the AVI format with a total duration of 7 hours and 15 minutes. Specially, a set of 1980 RGB videos of the AVI format are provided. There are two different indoor backgrounds. The backgrounds contain different scenes in which multiple persons pass or play basketball. The length of video sequences also varies. Although the depth, skeleton and silhouettes videos are also given, we only use the RGB videos to perform the tennis action recognition experiments.

2) Results: The five-fold cross-validation strategy is used to split the dataset to the training set and test set. We compared the proposed historical LSTM to the typical LSTM. The parameter $\tau$ of historical LSTM is fine tuned from 2 to 5. Table 2 shows the recognition accuracy values of the methods. As is shown in the table, when the parameter $\tau$ is set as 3, the average accuracy of the historical LSTM model achieves an accuracy of 0.74. Furthermore, the average accuracy of the historical LSTM model is 0.70 when the parameter $\tau$ is set as 2. When the parameter $\tau$ is set as 4, the historical LSTM model achieves an accuracy of 0.71. However, when $\tau$ is set as 5, the accuracy of historical LSTM decline to 0.63. It is seen that setting the parameter $\tau$ to a medium number according to the time period in the historical LSTM model is better. Meanwhile, the average accuracy of the LSTM model is 0.56. The experimental results show that the proposed historical LSTM model outperforms the LSTM model in the accuracy of perdition.

| Method                  | Accuracy |
|-------------------------|----------|
| Historical LSTM ($\tau = 2$) | 0.70     |
| Historical LSTM ($\tau = 3$) | 0.74     |
| Historical LSTM ($\tau = 4$) | 0.71     |
| Historical LSTM ($\tau = 5$) | 0.63     |
| LSTM                     | 0.56     |
| Mora et al.             | 0.47     |
| Gourgari et al. (using depth videos) | 0.6     |
| Gourgari et al. (using 3D skeletons) | 0.54 |

In [2], the authors performed experiments using the RGB videos on the THETIS dataset and get an average accuracy of 0.47 for tennis action recognition using a leave-one-out strategy. Compared to their experiments, we employ less training samples and obtain a better performance under a more difficult condition. In [3], the authors performed tennis action classification experiments using depth videos and 3D skeletons separately on the THETIS dataset and obtained accuracy 0.60 and 0.54 respectively. Compared to their results, our experiment use the raw images alone, which is a more challenge task. Experimental results prove that our proposed method is competitive and outperform the-state-of-art methods.

IV. Conclusion

This paper proposed a historical Long Short-Term Memory networks to model the historical information. The proposed historical LSTM was used for tennis action recapitication on the CNN features of local frame images of videos. Experimental results on the tennis action datasets demonstrate that our method is effective. Our future works will include the improving of the weighting strategy and more experiments on real tennis game videos.

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