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A Simple and Fast Action Recognition Method Based on AdaBoost Algorithm

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Abstract

A novel feature representation method based on AdaBoost algorithm is put forward for action recognition in this paper. The method can not only adequately describe action in complex scenarios, but also select the most discriminative sample subset from a large amount of raw features of training data. So it can realize a double result, that is, reduce the recognition computational complexity and achieve a good recognition accuracy. The pyramid histogram of oriented gradient feature (PHOG) descriptor is utilized to represent raw feature data. In order to select most discriminative samples subset, AdaBoost algorithm is used to extract the raw feature data. The nearest neighbor classifier algorithm is utilized to test the proposed method on the UCF Sports database. Experiment results show that the method not only achieve the better recognition rate but also greatly improve the speed of recognition.

***Keywords**: Pyramid histogram of oriented gradient; AdaBoost algorithm; Nearest neighbor classifier; UCF Sports database*

1. Introduction

Recently, visual analysis based on human action recognition has gained more and more attention which is contributed to its wide applications in many areas such as human-computer interaction, content-based video summarization, visual surveillance, analysis of sports events, and so on. Due to the complexity of the action, such as different wearing and habits leading to different observation of the sane action, the camera movement in the external environment, illumination change, shadows, viewpoint, and so on, these influences make action recognition still a challenging project [1-2].

Previous the representation of human action can be roughly divided into holistic and part-based approaches. Holistic methods first localize the person using a method of tracking or background subtraction and then make use of the global properties of 2-D located images along the time axis, depicting a human action [3-4]. Part-based approaches treat a space–time video volume as a collection of local parts, where each one consists of some distinctive motion patterns. Holistic representations recover a large of information about action human, but that they heavily rely on accurate person localization. Consequently, their applicability to complex scenarios is limited by their sensitivity to occlusions, noise and viewpoint. Moreover, pre-processing steps, such as background subtraction, segmentation, and tracking, are often required, which make it computationally expensive [5].

Thereby, in order to seek a more simple and discriminate representation for fast action recognition, many researches all focus on part-based approaches, such as the representation based on space-time interest points, optical flow method and Histogram of Oriented Gradients (HOG), *etc.* For representation based on space-time interest points, there is a key imperfection which has been indicated by many researchers that space-time interest points representations can be too local and fail to capture adequate spatial or temporal knowledge, especially in a real complex scenario. For improve the performance

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of interest points, Ren [6] *et al.* proposed a salient vocabulary construction algorithm based on the three dimensional scale invariant feature transform (3D SIFT) descriptor of space-time interest points to select representative visual words through K-means clustering from a global point. This approach achieves a good and fast recognition due to enhance the correlation of points and a neighboring point in the temporal domain, but do not get rid of the problem of missing information. And use K-means clustering to decrease the dimension of training samples that can make the rate of recognition enhanced, however, which is inevitable to bring to subsequent recognition error because that the selection of initial clustering centers and parameter K is unsupervised, only rely on experience.

Optical flow approach can achieve abundant motion information to fully characterize action, as everyone knows, but it is highly affected by different intensity of light. In order to avoid the disadvantages, Jiang [7] *et al.* introduced a fused shape-motion prototype-based approach. The histogram of oriented gradient feature (HOG) descriptor is used to form the shape information and Optical flow feature is applied to construct the motion characterization, then the combine feature is used to build an action prototype tree via hierarchical K-means clustering so that the dimension of combined feature can be decreased to reduce calculation cost in recognition. This technique of combined features can gain a rich action information and compensate the disadvantage of Optical flow under the complex scenes, but it is at the cost of a final feature with high dimension disaster apart from the drawback of K-means from [6]. The Histogram of Oriented Gradients (HOG) as a simple and strong robust representation can fully descript human action appearance characteristics in a real complex scenario–multiple regions, it has been experimentally proved to outperform other features to encode human figures in human detection [8]. So Jin Wang [9] *et al*. employ the Pyramid Histogram of Oriented Gradients (PHOG) improved based on HOG to characterize human figures for action recognition, and then Principal Component Analysis (PCA) is applied to reduce the dimension of feature vector to improve the rate of recognition. In this method, PHOG as a simple representation can capture a large number of human action information, which is more discriminated than HOG in structural characters. But solve the problem of high dimension with PCA only decrease the dimension of each samples data rather than the number of samples mainly affecting recognition rate, in addition, it can lead to some key data loss caused by keep only the main component of data. So an effective method decreasing the number of samples based on a simple, robust and fully characterized is applied to enhance the rate of recognition is crucial. Based on the point, Liu [10] *et al.* proposed AdaBoost algorithm to select the most discriminative sub-blocks feature from a great deal of raw sub-blocks data produced by gather 3D SIFT descriptor of each video sub-block. The method has an advantage over k-means and PCA that it can reasonable reduces the number of the training samples of each video according to sample weight to enhance recognition rate.

Based on the above analysis, for the sake of a simple, accurate and fast recognition system in real scenarios, PHOG and a novel AdaBoost algorithm selecting key frame in an action video are proposed in the paper, rather than sub-blocks of each video from [10]. As illustrated by Figure 1, firstly extract PHOG feature of each image of video clips from action dataset, and divide video clips PHOG feature data into two parts as the training samples owing multiple action classes and test samples, then apply AdaBoost algorithm to select some key frames images from each action class in the training videos, in this way, one action can be described by a handful of the most discriminative samples. Finally, test the extracted feature on real scene dataset using one more simple and fast the nearest classifier, the result demonstrate the proposed method not only remarkable improve recognition rate, but also efficiently raise recognition accuracy, create an accurate real-time recognition system in complex scene.

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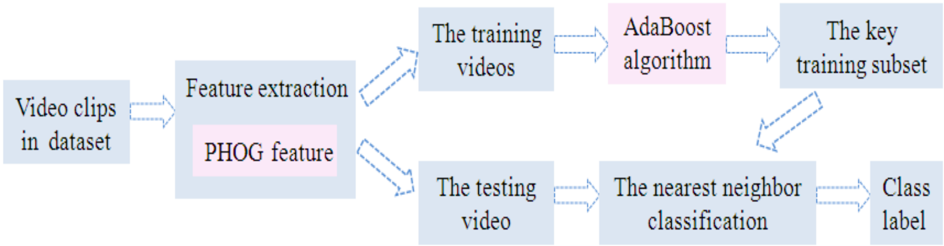

Figure 1. Schematic of Proposed Approach

2. Action Representation

As a result of the success of HOG for action recognition in complex scenarios has been proved by Guan Luo et al [11]. In this paper, a more rich and discriminative representation is utilized to encode human behavior in realistic environment. In addition, in order to improve the speed of recognition, reduce the number of training samples and achieve the most discriminative feature data is necessary. The following describes two processes of extract raw feature and select the key sub-samples.

2.1. The Raw Feature Extraction

The Pyramid Histogram of Oriented Gradients (PHOG) is an improved algorithm based on HOG, PHOG has a great advantage over HOG in terms of behavior description. Its principle is to divide an interest area into a number of cells at several pyramid levels. Gradient orientation on all pixels within each cell is accumulated to form a feature vector. All the histograms are concatenated to construct the final feature [9]. Specifically, firstly boxed the interesting region of each frame image of given an action video sequence and the magnitude $m(x,y)$ and orientation $\theta(x,y)$ of the gradient on each pixel (x,y) are calculated as and the pixels gradient distribution expresses in Figure 2(b), then divide gradient distribution into different sub-regions at every pyramid levels, that is 2×2, 4×4 and 8×8 cells respectively, as shown in Figure 2(c). Finally, gradient over all pixels within each cell project on 12 orientations to form a 12 feature vector, all sub-regions of every level are accumulated to form a $12\times2^l\times2^l$ ($l=1,2,3$ means the l .th level), as shown in Figure 2(d) (e). The feature vector produced by each level is concatenated to a final PHOG representation for a frame image.

$$\theta(x,y)=arctan\frac{g_x(x,y)}{g_y(x,y)} \tag{1}$$

$$m(x,y)=\sqrt{g_x(x,y)^2+g_y(x,y)^2} \tag{2}$$

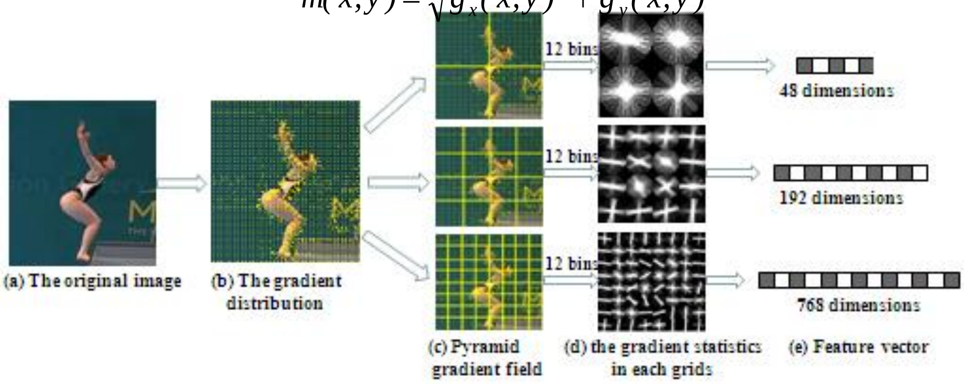

Figure 2. The Schematic of Extract PHOG Feature

2.2. AdaBoost for Raw Feature Selection

In the process of recognition, identify label mainly depend on the similarity of test sequence and training sequence, which is achieved by comparison between each frame image of test sample and all of training sample. Good recognition rate is achieved under the condition of a large of training data as usual, which not only leads to a low recognition speed but also has a less discriminative ability due to its groundless selection of training data. AdaBoost algorithm is used to extract the most discriminative samples in a large number of raw features, which can get a compact training dataset, consequently, a real-time detection system would be established as a result of the reduction of computational cost and the improvement of recognition speed.

Usually AdaBoost algorithm [12] as a kind of high accuracy classification method, its core idea is that the same training sample set according to the different training sample subset with the different sample distribution to train multiple weak classifier, then combine multiple weak classifier constitute a strong classifier. The algorithms are to change the corresponding weights of each sample according to each training sample and all the training sample classification accuracy, then change the distribution of the training sample and select the new training sample subset under the update of sample distribution, finally combining each weak classifier to make up a higher accuracy strong classifier according to certain rules. In the paper, the traditional AdaBoost algorithm is improved to select the most discriminative frame image from each class of action according to the sample weight, instead of construct a strong classifier. That is, given a training set $\{(x_1, y_1), .(x_j, y_j)..,(x_n, y_n)\}$ where x_i is the feature vector of each frame image and $y_i \in \{-1,+1\}$ is corresponding the action label, AdaBoost share each training set pattern a weight ω_j, initially all training samples to be equal. In the learning phase, a base classifier is trained and the label is assigned to every pattern. Training set patterns which are incorrectly predicted have their weights increased by some factor and the weight of correctly predicted patterns are decreased. Training of a new base classifier is repeated with the new set of weight in a scheme, whereby with increasing numbers of iterations, patterns which are consistently difficult to classify correctly acquire large weight values (and easy-to-classify patterns acquire small weight values) [13]. We thus select the patterns with the small-lest final weights values to form the highly discriminative feature, listed by reference Figure 3 as follow:

The training sample set: $(x_1, y_1), \ldots (x_j, y_j), \ldots (x_n, y_n)$, $y_j \in \{1,-1\}$; x_j is each image feature data of the total training samples, y_i is corresponding action label, and treat the selected class samples as 1, all others with -1.

- Initialize weight：$\omega_1(j) = \frac{1}{n}$ (sample distribution ω)
- Iterative process($T=1,2,\ldots,T$)：

(1) Randomly select five video samples from the selected action class and 5 five videos in each action from all other of video samples as the known samples.

(2) Input the total samples and the known samples subset into the nearest neighbor classifier, then each sample of the total training samples can be achieved a hypothesis $h_t(x_j) \in \{1,-1\}$ the error is calculated with respect to $\varepsilon_t = P_{D_t}(h_t(x_j) \neq y_j)$;

(P_{D_t} is value of error sample), calculate the weight of this weak classifier:

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$$

(3) Update the weight each pattern of the total training samples:

$$D_{t+1}(j) = \frac{D_t \exp(-\alpha_t y_j h_t(x_j))}{Z_t}$$

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● Selecting feature data with the small weight value from the labeled 1 sample.

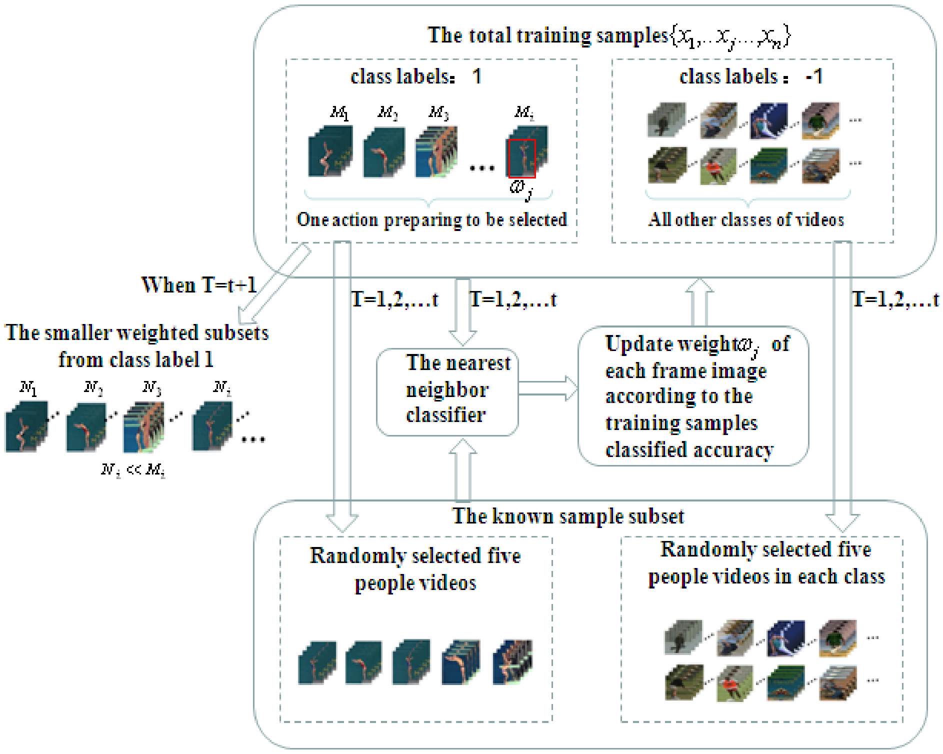

Figure 3. The Selection Process of Adaboost Algorithm

Through the above process, a small amount of the most discriminative feature data describing one class action have been selected, repeat the same operation for other classes until complete all action in dataset, make preparation for the following action recognition.

3. Classifier Design

The nearest neighbor classify algorithm is not only a simple and effective identification method, but also has a fast recognition speed. In order to realize the real-time detection, identify the extracted features using the nearest neighbor classifier, as follows:

Supposing that there are c classes as $w_1, w_2, ..., w_c$,each class has the number of N_i ;marked samples, then the discriminant function of class w_i is as Eq. 3.

$$g_i(x) = \min_k \left\| x - x_i^k \right\|, k = 1,2,...,c \tag{3}$$

The subscript i of x_i^k means class w_i, and k is the k the sample among total N_i in classes w_i .According to Eq.3, the decision rule can be defined as the following

$$If \quad g_j(x) = \min_k g_i(x), i = 1,2,..,c \quad So \quad x \in w_j \tag{4}$$

This decision method is called nearest neighbor method, and the Euclidean distance between samples is:

$$D = \sqrt{\sum_{i=1}^{N} (A_i - B_i)^2} \tag{5}$$

A and B are feature vectors and N is the number of the feature vectors.

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1NN in this paper experiments is also called frame by frame nearest neighbor, to be specific, each action sequence has a correct classification symbol, and 1NN classifier try to forecast the symbol of test action sequences to be one action type with the most similarity using closest distance. We classify the training samples to relevant action classes, for example ten classes, so in each action class there will be the same actions of different actors (the frame number of each action can be different). Then respectively calculate the Euclidean distance between each test frame feature (the same action sequence in test sample) and each training frame feature make the classification recognition according to the nearest neighbor decision rules. Of course here we compare the distance between each frame, the frame with minimum distance in the training samples will vote for the action type which it belongs to. All the frames in test samples are in turns carried out using the distance calculation and voting choices above, finally our test sample action type will be the action class symbol which has the highest votes [14].

4. Algorithm Verification and Results Analysis

In this section experiments are performed on the UCF Sports dataset with the AdaBoost selection based on PHOG feature descriptor of each frame of video sequence. By comparing it with the same methods without AdaBoost and the most recent reports associated with the same dataset, the outstanding performance of the proposed algorithm is demonstrated in this paper.

4.1. The Raw Feature Extraction

To test the availability of our approach, using the public UCF Sports dataset, which is challenging due to its large variations in human body, scale, appearance, view angle, occlusions, cluttered backgrounds, variations in scale and motion discontinuity. The dataset contains 150 broadcast sports video sequences (at a resolution of 720×480), which are collected from different broadcast sports channels, for example BBC and ESPN. As presented in Figure 4, there are 10 action types in the dataset.

Figure 4. Example Video Clips from the UCF Sports Dataset: (a) Diving, (b) Golf-Swinging, (c) Kicking, (d) Lifting, (e) Riding, (f) Running, (g) Skating, (h) Swinging-2, (i) Swinging-3, (j) Walking

4.2. Testing Result

Extract feature on three levels according to Section 2.1, and the feature vector on each level are concatenated to a final PHOG representation for a frame image, a 48+192+768 vector. In order to test feasibility of PHOG, leave-one-out cross validation method is adopted, that is, use each video as a test sample in turn, and the rest of all the videos as the

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training, circulation continued until all actors are completed testing by the nearest neighbor classifier algorithm. The confusion matrix of recognition results is shown in Figure 5.

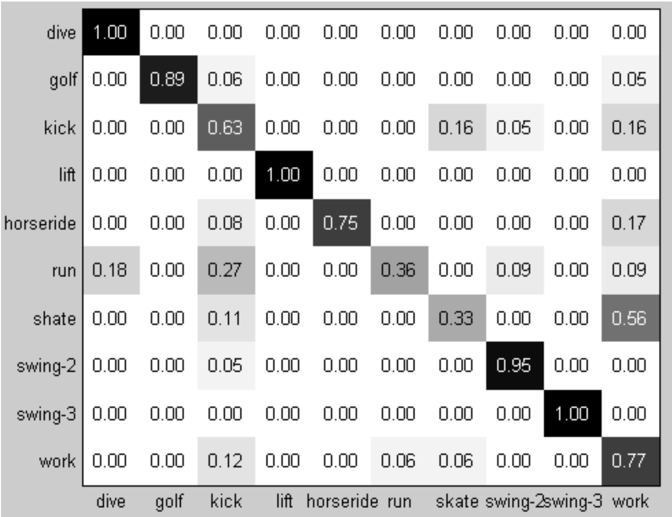

Figure 5. The Confusion Matrix of Recognition Results PHOG Feature

The average recognition rate is 76.8%, as seen from the above confusion recognition result, there is no enough good result for some action due to the interference of light and background, *etc.* On this point, the process of calculate the distance in the nearest neighbor classifier can be improved to share every level feature a different weight, because that the third level feature with 8×8 cells is a more abundant information than the first, and which has the most important contribution assigned a bigger weight for recognition. According to Eq.3, the weighted Euclidean distance based on the three pyramid structure between samples is:

$$L = \partial_1 D_1 + \partial_2 D_2 + \partial_3 D_3 \tag{6}$$

D_1, D_2, D_3 is the Euclidean distance produced by the single first, second and third layer feature between samples respectively, $\partial_1, \partial_2, \partial_3$ is corresponding weight of each of the three levels. In order to get better recognition accuracy, a set of appropriate weights is adopted by repeated experiments to improve the recognition result, as shown in the Table 1, the recognition accuracy is corresponding to different weights.

Table 1. The Recognition of the Different Combination of Weight

∂_1	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**	**0.2**
∂_2	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**	**1**
∂_3	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Recognition accuracy(%)	**80.57**	**82.09**	**82.09**	**82.09**	**80.54**	**80.02**	**80.85**	**81.76**	**80.85**	**80.85**

As seen from the above table, the weighted method significantly increase the ability to recognize, demonstrated the feature with weight of each level have a more discrimination power. However, up to now, due to the large number of training samples, the recognition rate is an unsolved problem. So AdaBoost algorithm based on the PHOG is proposed to select the most discriminative frames image in each class of action, so that the significantly improvement of recognition rate is caused by the reduced training simples quantity. In the process of selection, according to Section 2.2, select N ($N=\frac{1}{2}M$ or $N=\frac{3}{4}M$) frames from each class of the raw feature respectively under $\partial_1, \partial_2, \partial_3 = 0.2, 0.4, 1$. For verify the performance of AdaBoost algorithm, input the testing sample with weights and selected N key sub-simples into the nearest classifier as well, and find the best result under a set of appropriate weights. The Table 2 shows that the average recognition result achieved by different weight combination when and,

Table 2. The recognition of the Different Weight Combination when $N=\frac{1}{2}M$ and $N=\frac{3}{4}M$

	$N=\frac{1}{2}M$					$N=\frac{3}{4}M$				
∂_1	0.1	0.1	0.1	0.3	0.4	0.5	0.1	0.2	0.3	0.4	0.5
∂_2	0.2	0.4	0.4	0.6	0.6	0.6	0.2	0.4	0.6	0.6	0.6
∂_3	0.6	0.6	1	0.9	0.8	0.7	0.6	1	0.9	0.8	0.7
Recognition accuracy (%)	78.18	78.18	77.62	79.61	79.68	78.24	83.72	82.36	70.53	82.95	84.00

Table 3. The Recognition Accuracy and Time of Different Number of Training Samples

frames	The best recognition accuracy (%)	The fast recognition time (s/frame)
M	82.09	0.3138
$N=\frac{1}{2}M$	79.68	0.1567
$N=\frac{3}{4}M$	84.00	0.2307

Table 3 expresses that the best recognition accuracy and time produced by the selected different number of training samples, compared with the recognition result of unselected training samples. Finding that, AdaBoost algorithm used for select the most discriminate samples contributes to a conspicuous improvement of recognition rate over the raw feature. When $N=\frac{1}{2}M$, the accuracy of recognition has a slight decrease due to the excessive reduction of training samples leading to the loss of the important data. However, when $N=\frac{3}{4}M$, it can appropriate to reduce raw training samples, and reserve the most discriminated data as the decrease of training samples. Hence, it not only improves the recognition rate, but also achieves a best recognition accuracy. In order to future explain the discriminate owed by a small number of selected sub-samples gained by AdaBoost, Figure 6 shows the confused recognition matrix of unselected and feature and selected sub-samples $N=\frac{3}{4}M$. In run and skate, the improvement of recognition performance is contributed to reject the poor separability samples and retain the key frames feature.

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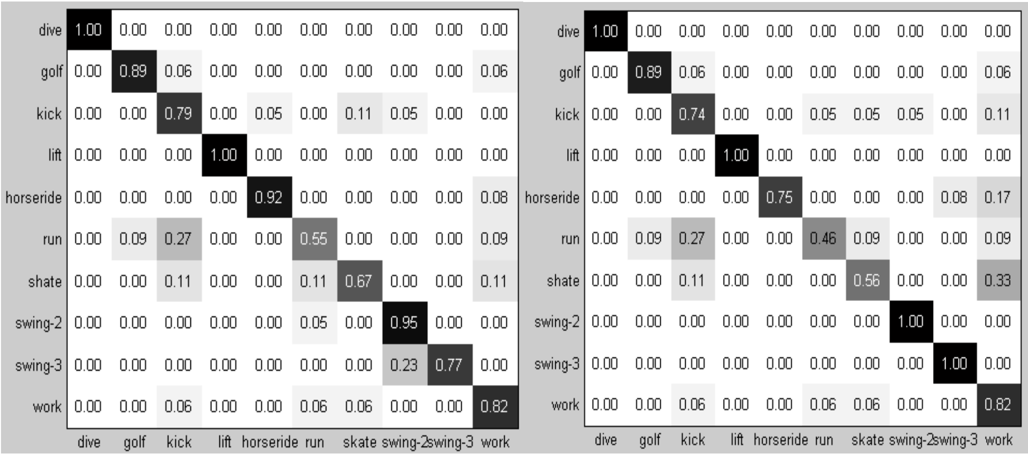

(a) The Results without Adaboost (b) The Results with Adaboost

Figure 6. The Confused Recognition Matrix with the Best Recognition Accuracy

The comparisons of performance between the proposed method and the recent related works based on UCF Sports dataset are shown in Table 4. Obviously, our approach has a good recognition result. Although the recognition rate of [5,18,20] has a slightly higher than ours, the processes of exacting feature and action recognition are very complicated, which inevitably bring to a vast number of calculation and time-consuming. However, our approach not only achieve a good recognition rate but also possess a simple feature representation and a rapidly recognition. So our method outperforms all of other state of methods.

Table 4. Comparison with Related Work on the UCF Sports Dataset in Recent Year

Literature	Year	Method	Accuracy
Yan song [7]	2010	The local spatial temporal(ST) feature +GMM+NNC	73.67%
Muhammad Muneeb Ullah[15]	2012	The trajectories of body joints based on HOF +BOW+SVM	83.13%
Zhong Zhang[16]	2012	HOG and HOF of interest point+K-means+context-constrained linear coding+SVM	87.33%
Amir Farid Aminian Modarres[17]	2013	A new graph-based posture(BPG) descriptor+HMM	56.67%
Leonardo Onofri[5]	2013	A multiple subsequence combination(MSC)+MoSIFT+BOW+SVM	88.00%
Amir Farid Aminian Modarres[18]	2013	The relation XYT coordinates of interesting points+GMM+appearance information+BOW+traject +HOG+MBH+LSSVM	91.98%
Our approach	____	PHOG+AdaBoost+NNC	84.00%

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5. Conclusion

In order to reduce the number of training samples to realize a real-time action recognition system, firstly a simple and discriminative feature representation (PHOG) was chosen as the raw feature data, and then share a weight to PHOG at each level, AdaBoost algorithm was utilized to select a small number of effective features from the raw feature data under the optimal set of weights. Finally through compare the recognition result of different frames, finding that the recognition time decreased along with the reducing of the training frames. When the frames is of the raw feature, a better and faster recognition result is achieved simultaneously. The experiment results certified the feasibility and effectiveness of the algorithm proposed in this paper. Our future work is combining PHOG feature descriptor with one or two high robust characteristic representation algorithm to improve the recognition rate on the UCF Sports.

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