A Joint Evaluation of Different Dimensionality Reduction Techniques, Fusion and Learning Methods for Action Recognition[☆]

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Abstract

This paper addresses the problem of action recognition with improved dense trajectories (IDT). Recently, IDT achieved a significant performance in action recognition with realistic videos. However, the efficiency of storage and the speed of classification are limited due to the dense samples in feature space. To address this issue, the intuitive way is to reduce the dimension and adopt a fast classification method. Therefore, we explore the influence of dimensionality reduction on the recognition rate. In addition, Extreme Learning Machine (ELM) is adopted to further improve classification efficiency. We present performance on the KTH, UCF11, HMDB51, and UCF101 datasets in all kinds of situations such as the different fusion methods, the different dimensionality reduction, and different learning methods. As a result, it can be observed that ELM with principal components analysis (PCA) improves the performance in terms of mean average precision (mAP) which not only significantly reduces computational cost but improves accuracy. What's more, the training and testing time decrease 1—2 orders of magnitude without losing accuracy when Fisher vector (FV) adopts reduction techniques before it fed into classifier.

Keywords: human action recognition; different fusion methods; different dimensionality reduction; different machine learning methods; video signal

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processing;

1. Introduction

Action recognition has caught the attention of researchers from real-time video surveillance and security monitoring, automatic video indexing, and human-computer interfaces. Meanwhile, the problem of action recognition in videos is
5 challenging, and all difficulties associated with object detection and recognition task, such as large intra-class variations, low resolution, camera motion, view point changes, geometric and photometric variances, may also be encountered in action recognition.

In recent years, dense sampling has great potential in improving recognition
10 rate over sparse interest points [1]. Wang et al. [2][3][4] proposed an approach to describe videos by dense trajectories (DT) which has a significant improvement over the state of the art on some realistic data sets with fisher vector (FV). However, the DT based representation is expensive in memory storage and computation due to the large number of densely sampled points. What's
15 more, they need to combine all the descriptors which are histogram of oriented gradients (HOG), histogram of optical flow (HOF), motion boundary history (MBH) and trajectory (Dentr) to obtain the best results, and the efficiency is also a problem for the dense trajectories and FV dimension. Hence, Murthy et.al. [5] proposed to select only a few dense trajectories and evaluate it on the
20 complex dataset with improved performance. In this paper, we apply principal component analysis (PCA) or linear discriminant analysis (LDA) to reduce the dimension for local descriptor and video-level vector (i.e., FV in this paper), respectively. Finally, we evaluate all kinds of fusion methods which fuse those descriptors by probability fusion, video-level fusion or local feature fusion.

25 As local features' discriminative power is low and its data is large which limit the efficiency and memory usage, it is difficult to directly classify the local features (i.e., low-level representation). Hence, three main vector aggregation methods (i.e., Bag of features, Fisher Vector, VLAD) are used for action recog-

nition [6]. Bag of features (BOF) is popularly used for aggregating local cuboid
 descriptors into compact codes [2][7][8][9]. However, it only encodes the zero
 statistics information and lacks structural information. Therefore, the fisher
 kernel (i.e., fisher vector) is used for large-scale image classification [10] and ac-
 tion recognition [3]. Fisher vector (FV) encodes both first and second statistics
 between the video descriptors and a Gaussian Mixture Model (GMM). Vector
 of locally aggregated descriptors (VLAD) was first proposed by Jegou in [11] for
 image search and index which was thought as a simplification of the fisher vector.
 This technique was first considered by Jain et al.[12] for action recognition. In
 paper [10] it shows that the fisher vector was more suitable than BOF for large-
 scale image classification, which achieves better results for action recognition in
 [3]. In addition, FV only needs to use a linear SVM for classification which is
 efficient. Therefore, FV is used in our paper. However, for each descriptor, a
 2DK dimensional FV is used to represent it. Where D is the descriptor dimen-
 sion, K is the number of Gaussian Mixture Model (GMM). To better fit FV
 encoding, PCA is used to reduce the descriptor dimensionality. Normally, the
 value of K is set to be 256 for action recognition to ensure the performance and
 efficiency[3][5], however, 512D it is still large for each descriptor's FV. There-
 fore, before FV feeds into classifier, dimensionality reduction technique can be
 applied to FV to improve efficiency and save storage. In this paper, we evaluate
 the influence of different dimensionality reduction technique in terms of mean
 average precision (mAP) for action recognition. From the experiment, it shows
 that FV adopts dimensionality reduction which can guarantee or improve the
 performance and efficiency.

In action recognition for different vector-level representations, classifier main-
 ly uses χ^2 kernel or linear support vector machine (SVM)[2][13][14][15][16]. For
 large-scale datasets, due to the increase number of training samples, the effi-
 ciency of SVM will decrease. Therefore, in our paper, we will use the Extreme
 Learning Machine (ELM) for action classification. The fast and efficient ELM
 was used by Iosifidis et.al [17], Minhas et.al[18] and Varol et.al[19] for action
 recognition, but the usage of ELM in the action recognition area is still rare.

60 Hence, in our paper, we not only uses ELM but compares it with SVM for action recognition.

This paper is organized as following: in section II, we analyze the related work. We establish the framework and expatiate our method for action recognition in section III. The experimental results are presented in Section IV. Finally,
65 we make a conclusion of this paper in section V.

2. Related work

Various work has studied the problem of based-video human action recognition. In this section, we give an overview of previous work which is most relevant to our proposed method.

70 Improved dense trajectories (IDT) [3][20][21] was popularly used for action recognition with realistic videos on account of significant performance. Due to the large number of densely sampled points, the IDT based representation is expensive in memory storage and computation. Therefore, it is important to improve the efficiency of memory storage and computation. Shi et al. [22][23]
75 adopted PCA to local feature descriptor for better fit FV encoding. Ikizler et al. [24] first applied LDA to obtain a more compact and discriminative feature representation. These methods have been proved quite successful to reduce the dimension of local feature that is better for FV encoding. LDA is a popular method for extracting features that preserves class separability. However it is expensive in memory usage and computation. Hence, Cai's[25] LDA which is
80 called Spectral Regression Discriminative Analysis (SRDA) is used in our paper. SRDA only needs to solve a set of regularized least squares problems, and there is no eigenvector computation involved, which saves both time and memory highly. FV's dimension is 2DK which is larger than the BOW. In this paper, we
85 concentrate on how to reduce the dimension of FV before it feeds into classifier.

Although only linear SVM classifier is needed to classify FV, it is expensive for large-scale dataset such as HMDB51 [26], UCF101 [27]. Therefore, a faster classifier is used in this paper to improve the efficiency. ELM was used for

action recognition in recent years [17][18][19]. Iosifidis et al. [17] proposed a
 90 discriminant ELM algorithm to exploit information appearing in both labeled
 and unlabeled action instances. Minhas et al. [18] and Varol et al. [19] used
 ELM for action recognition with large-scale dataset. Though ELM is fast and
 efficient, it is rarely used for action recognition. Thus, in this paper, we explore
 its efficiency and performance for action recognition.

95 3. Our framework

In this paper, we discuss our framework in three parts. First, we introduce
 the basic flow chart (see Fig.1). Second, we discuss the different fusion methods
 used in this paper which include local feature fusion, mid-level fusion, and clas-
 sifier results fusion (called the late fusion). And the first two fusion we generally
 100 call it early fusion. Third, we briefly introduce the machine learning methods
 which are used in our paper.

Figure 1: The data-flow for our action recognition system

3.1. The basic flow chart for action recognition

3.1.1. Local feature descriptors of dense trajectories

In this paper, we use the low-level representation which was proposed by
 105 Wang [3]. For those descriptors, we use PCA to reduce the number of features

such as HOG, HOF, MBH and Dentr which is the trajectory descriptor proposed in paper [3] for better fit FV encoding. The data-flow is shown in Fig.1.

First, dense trajectories are extracted from eight spatial scales. Feature points are sampled on a grid spaced by W pixels and tracked in each scale separately. Then, the sampled points are tracked by applying median filtering over the dense optical field. The MBH, HOG, HOF and Dentr were computed on the neighbourhood of the points derived by the dense trajectories. In our experiment, we use the default $W=5$ pixels. The work in [3] shows that the space-time volumes (spatial size 32×32 pixels) around the trajectories are divided into 12 equal-sized 3D grids (spatially, 2×2 grids and temporally, 3 segments). For both HOG and HOF, orientations are quantized into 8 bins using full orientations, with an additional zero bin for HOF (i.e., in total 9 bins). MBH are computed separately for the horizontal and vertical components of the optical flow. Thus, the HOG descriptors have 96 dimensions, HOF descriptors have 108 dimensions and MBH descriptors have 192 dimensions. For $L=15$ which is the trajectory of given length, the trajectory obtained a 30 dimensions. In order to improve memory storage and computation, we apply PCA for those descriptors which is reduced to 64, 64, 128, 20, respectively for place2 and place3 fusion. While for place1 fusion we combined the local features together that have 426 dimensions. In this situation, we apply PCA for it to reduce to 200. What's more, PCA can improve performance by decorrelated data.

3.1.2. Aggregating method

As we know, Fisher vector (FV) was popularly used for action recognition in recent years [5][28][16][29]. Because FV representation has a lot of advantages, such as training fast and improving the accuracy for large-scale action recognition. Therefore, we adopt FV aggregating methods in this paper.

We directly aggregate HOG, HOF, MBH and Dentr by Fisher kernel, to obtain the FV. The Fisher kernel (FK) is a generic framework which combines the benefits of generative and discriminative approaches. The FK produces fisher vector which is the gradient of the sample's likelihood with respect to the

parameters of this distribution. Let $v = (X_1 \dots X_N)$ be a set of D dimensional features vectors (e.g. HOG, HOF, MBH, etc.) extracted from a video. Let $\Theta = (\mu_k, \Sigma_k, \Pi_k : k = 1, \dots, K)$ be the parameters of a Gaussian Mixture Model (GMM) fitting the distribution of descriptors, among which $\mu_k, \Sigma_k, \text{ and } \Pi_k$ are respectively the mean vector, covariance matrix and mixture weight. We assume that the covariance matrices are diagonal and denote by σ_k^2 the variance vector. The GMM associates each vector X_i to a mode k in the mixture with a strength given by the posterior probability:

$$q_{ik} = \frac{\exp \left[-\frac{1}{2} (X_i - \mu_k)^T \Sigma_k^{-1} (X_i - \mu_k) \right]}{\sum_{t=1}^K \exp \left[-\frac{1}{2} (X_i - \mu_t)^T \Sigma_t^{-1} (X_i - \mu_t) \right]} \quad (1)$$

For each mode k , considering the mean and covariance deviation vectors

$$u_{jk} = \frac{1}{N \sqrt{\Pi_k}} \sum_{i=1}^N q_{ik} \frac{X_{ji} - \mu_{ik}}{\sigma_i} \quad (2)$$

$$v_{jk} = \frac{1}{N \sqrt{\Pi_k}} \sum_{i=1}^N q_{ik} \left[\left(\frac{X_{ji} - \mu_{ik}}{\sigma_i} \right)^2 - 1 \right] \quad (3)$$

where $j = 1, 2, \dots, D$ spans the vector dimensions. The FV of videos v is the stacking of the vectors u_k and the vectors v_k for each of the K models in the Gaussian mixtures:

$$\Phi(V) = [\dots u_k \dots v_k \dots]^T \quad (4)$$

where $[\bullet]^T$ means the transpose of vector. Hence, each video is represented by a 2DK dimensional FV for each descriptor type. Before being fed into classifier, we use FV by applying the signed square-rooting and following with L2 normalization.

The work in [30] shows that the mAP increases with the K for image search. However, for the high value of K , the dimensionality of the fisher vector becomes very large and is not suitable for high efficiency. Therefore, we apply LDA or PCA technique before FV is fed into classifier. Finally, linear classifiers are used to classify the action.

3.2. Different fusion methods

As we know, single feature only emphasises on a part of aspects of actions or
context information, such as HOG which captures the appearance information,
and HOF which captures the motion information. Hence, It is an important
issue to know how to combine them. Marszalek et al. [15] combined HOG\HOF
to increase recognition rate for Hollywood1 dataset. Early fusion was popularly
used for action recognition in [31][32][33][34][35]. While late fusion research is
rarely considered for action recognition in recent years. In this paper, we apply
different fusion methods to improve the recognition rate and compare them.

For each descriptor, early fusion and late fusion are respectively used to
combine them. And, there are two places to fuse the descriptor for early fusion,
which are place1 (local feature fusion) and place2 (video-level fusion) fusion,
respectively, as shown in Fig.1. Late fusion is corresponding to place3 in Fig.1.
Meanwhile, in [16], which are also namely descriptor-level fusion, kernel-level
fusion and score-level fusion.

Place1 fusion combines the Space-Time interest points (STIP) features (see
the Dotted arrows of the Fig.1 after the box of place1 fusion); place2 fusion
combines FV representations (see the point arrows of the Fig.1 after the box of
place2 fusion). Before being fed into classifier, the combination of FV further
adopt LDA or PCA to reduce the dimension. And place3 fusion combines the
output of classifiers. In this paper, we will evaluate the three fusion methods
respectively, which shows that place2 fusion will be better than place1 and
place3 fusion except the case of ELM in UCF11.

3.3. Different machine learning methods

For each descriptor's FV, the linear classifier will be used to classify them
which has low cost [3][12]. In our experiment, we set the regularization param-
eter by cross-validation. Two different linear classifiers (SVM and ELM) are
adopted for descriptor's learning.

In machine learning, support vector machines are supervised learning models
associated with learning algorithms that analyze data and recognize patterns,

used for classification. For FV representations, linear SVM classifier is suitable for classification [10][16][28]. In our paper, first, we used the popular method
185 which is SVM for FV representation. For probability fusion of late fusion, the training is performed with probability models, which provide the probability estimates for testing. From the experiment, it shows that the training and testing time (not including pretreatment time in our paper) are expensive for large-scale dataset, therefore, we try to use the ELM machine learning methods.

190 Extreme Learning Machine is proposed by Huang et al. as an extremely fast alternative to other conventional popular learning algorithms [36]. The proposed algorithm works for the generalized single-hidden-layer feed-forward networks, but the difference is that the hidden layer in ELM does not need to be tuned [37]. [17][18][19] used ELM for action recognition. In our method, we
195 use linear kernel ELM and the parameter was selected based on cross-validation on the training set of the different datasets.

In our paper, for late fusion of SVM, we explore the different modes to combine those classifiers which are trained by all kinds of descriptors. It has six rules to combine those classifiers which are sum, product, max, min, majority,
200 median, respectively [29]. What's more, for ELM, we also use the same rules as SVM. The rules input is probability for SVM, while the scores as input for ELM. In the case of multi-class classification, we use a one-vs-one strategy.

4. Experimental results and analysis

In this section, we introduce the KTH, Youtube (UCF11), HMDB51 and
205 UCF101 dataset. Then, we analyze our results and list confusion matrix of the best result. The first combination (Comb.1) is corresponding to HOG, HOF and MBH descriptor, and the second combination (ALL_combine) is corresponding to Dentr, HOG, HOF, and MBH. In the place1 fusion we use ALL_combine, while the Comb.1 and ALL_combine are all evaluated in the place2 fusion. For
210 fast classification and to improve accuracy, we use LDA and PCA for FV representations, respectively in the place2 fusion and the rate is fixed for 100%. In the

Figure 2: The type of actions on KTH [39]

place3 fusion only the Comb.1 is evaluated. Furthermore, the best performance among every table is shown in boldface.

The efficiency of dimensionality reduction techniques is only compared to UCF11 dataset. Because in constrained dataset the efficiency problem does not exist, and in large-scale dataset it is very time consuming and require good hardware condition without reduction techniques. For simplicity, in table 5 tr_time and te_time mean training and testing time respectively.

4.1. Experimental setups

The KTH dataset contains 25 people for 6 actions (see Fig.2) (running, walking, jogging, boxing, handclapping and handwaving) in 4 different scenarios (indoors, outdoors, outdoors with scale changes and outdoors with different clothes). It contains 599 videos, of which 399 are used for training, and the rest for testing. It should contain 600 videos but one is missing. The evaluation condition is the same as [38].

The Youtube dataset [40] contains 11 (UCF11) action categories: biking, cycling, diving, golf swinging, soccer juggling, trampoline jumping, horse riding, basketball shooting, volleyball spiking, swinging, tennis swinging, and walking with a dog (see Fig.3). This dataset is challenging due to large variations in camera motion, object appearance and pose, object scale, viewpoint, cluttered background and illumination conditions. The dataset contains a total of 1,168

Figure 3: The type of actions on UCF11 [40]

sequences. We follow the original setup using Leave-One-Out Cross-Validation for a pre-defined set of 25 groups. Average accuracy over all classes is reported as the performance measure.

HMDB51 [26] is composed of 6849 video clips which are divided into 51 action categories. The action categories can be grouped in five types: 1) General facial actions (4): smile, laugh, chew, talk; 2) facial actions with object manipulation (3): smoke, eat, drink; 3) general body movements (19): cartwheel, clap hands, climb, climb stairs, dive, fall on the floor, backhand flip, handstand, jump, pull up, push up, run, sit down, sit up, somersault, stand up, turn, walk, wave; 4) body movements with object interaction (18): brush hair, catch, draw sword, dribble, golf, hit something, kick ball, pick, pour, push something, ride bike, ride horse, shoot ball, shoot bow, shoot gun, swing baseball bat, sword exercise, throw; 5) body movements for human interaction (7): fencing, hug, kick someone, kiss, punch, shake hands, sword fight. Some of the actions with this dataset see Fig.4. The different actions have large appearance variations. It all adopts the default training and testing splits [26].

UCF101 [27] has 101 action classes. The action classes can be divided into five types: human object interaction, body-motion only, human-human interaction, playing musical instruments, and sports. Totally, it has 13,320 video clips. To the best knowledge, this dataset has been the largest dataset so far. We perform evaluation on the first split of UCF101 according to the default

Figure 4: Some type of actions on HMDB51 [26]

Figure 5: compare different reduction techniques and learning methods

training and testing splits.

4.2. The performance of different dimensionality reduction techniques

255 In this section, we evaluate the impact of LDA and PCA on mAP and training\testing time for video-level representation (in this paper, it is FV). Table 1 and table 2 shows that PCA has no impact on the mAP but it is fast for classification see table 6 (non_PCA means that there is no dimensionality reduction for FV). It shows that the efficiency of LDA or PCA can be increased 1—2
260 orders of magnitude compared to non_PCA with SVM on UCF11. Therefore, in order to save computation cost and memory while preserving the accuracy, PCA will be used to be compared with LDA in the subsection for different datasets, different fusion methods and learning methods in table 1-4.

Seen "yellow and blue bar" of fig.5, LDA with SVM achieved the similar or
265 better performance than PCA with SVM except the Dentr's FV of HMDB51.

Table 1: dimensionality reduction technique comparison on the KTH dataset with different learning methods and fusion methods

learning methods →	SVM				ELM			
descriptor	LDA		PCA	non_PCA	LDA		PCA	
Dentr	91.67%		91.20%	91.20%	91.20%		91.67%	
HOF	94.91%		95.37%	95.37%	94.91%		94.44%	
HOG	93.52%		93.06%	93.06%	93.06%		93.98%	
MBH	96.30%		96.30%	96.30%	96.30%		96.30%	
place1 fusion	96.76%		97.22%		96.76%		96.76%	
place2 fusion	LDA	PCA	LDA	PCA	LDA	PCA	LDA	PCA
Comb.1	96.76%	97.22%	96.30%	96.30%	95.83%	95.83%	94.91%	96.76%
ALL_combine	96.30%	96.30%	96.30%	96.30%	95.37%	95.37%	95.37%	96.30%
place3 fusion ↓	LDA		PCA		LDA		PCA	
product	97.22%		96.76%		94.91%		92.59%	
sum	97.22%		96.76%		95.83%		96.76%	
max	96.76%		96.30%		95.83%		96.76%	
median	96.76%		96.30%		96.30%		96.76%	
min	96.76%		96.76%		94.91%		95.83%	
major	96.76%		96.30%		96.30%		96.76%	

Table 2: dimensionality reduction technique comparison on the UCF11 dataset with different learning methods and fusion methods

learning methods →	SVM			ELM			
descriptor	LDA		PCA	non_PCA	LDA		PCA
Dentr	76.07%		76.29%	76.29%	76.23%		77.02%
HOF	85.97%		85.73%	85.73%	86.39%		86.15%
HOG	84.61%		80.97%	80.97%	85.22%		85.02%
MBH	88.49%		87.48%	87.48%	88.20%		88.94%
place1 fusion	87.998%		86.761%		87.80%		87.76%
place2 fusion	LDA	PCA	LDA	PCA	LDA	PCA	LDA PCA
Comb.1	91.47%	90.18%	90.98%	88.76%	91.80%	91.71%	92.25% 91.94%
ALL_combine	91.14%	91.14%	90.54%	88.25%	91.56%	91.48%	90.80% 91.23%
place3 fusion ↓	LDA		PCA		LDA		PCA
product	90.43%		90.04%		86.44%		87.18%
sum	90.95%		90.05%		92.07%		92.51%
max	90.88%		89.31%		90.17%		90.91%
median	90.11%		88.67%		90.68%		91.46%
min	89.60%		87.86%		90.09%		91.15%
major	89.43%		87.91%		90.34%		90.52%

Table 3: dimensionality reduction technique comparison on the HMDB51 dataset with different learning methods and fusion methods

learning methods →	SVM				ELM			
descriptor	LDA		PCA		LDA		PCA	
Dentr	27.34%		37.6%		27.39%		32.66%	
HOF	46.06%		45.82%		46.17%		47.17%	
HOG	36.43%		35.90%		36.45%		37.996%	
MBH	49.50%		45.29%		49.13%		49.41%	
place1 fusion	22.353%		35.21%		22.244%		40.436%	
place2 fusion	LDA	PCA	LDA	PCA	LDA	PCA	LDA	PCA
Comb.1	55.14%	55.29%	55.32%	49.67%	54.42%	54.42%	54.55%	55.42%
ALL_combine	55.80%	55.71%	56.27%	50.57%	54.77%	54.79%	55.84%	56.47%
place3 fusion ↓	LDA		PCA		LDA		PCA	
product	55.25%		51.74%		30.98%		53.09%	
sum	54.75%		51.24%		54.49%		55.03%	
max	50.35%		48.80%		46.43%		48.54%	
median	54.03%		50.35%		50.44%		53.31%	
min	50.39%		48.28%		47.8%		50.35%	
major	49.54%		47.58%		49.39%		49.87%	

Table 4: dimensionality reduction technique comparison on the UCF101 dataset with different learning methods and fusion methods

learning methods →	SVM				ELM			
reduction method	LDA		PCA		LDA		PCA	
place1 fusion	75.549%		73.381%		80.518%		80.782%	
place2 fusion	LDA	PCA	LDA	PCA	LDA	PCA	LDA	PCA
Comb.1	75.4692%	75.76%	78.14%	76.42%	83.72%	83.72%	84.64%	84.77%
ALL_combine	75.416%	75.839%	78.00%	75.97%	83.69%	83.69%	83.94%	83.98%
place3 fusion ↓	LDA		PCA		LDA		PCA	
product	75.92%		77.06%		64.23%		81.81%	
sum	76.58%		76.95%		83.56%		83.69%	
max	76.13%		76.02%		76.34%		78.80%	
median	74.73%		75.63%		79.80%		81.87%	
min	68.78%		73.80%		76.66%		78.69%	
major	73.57%		74.14%		79.01%		79.46%	

On the other hand, "red and green bar" of Fig.5 shows that LDA with ELM obtains weaker performance than PCA with ELM. From "yellow and red bar" of Fig.5, it obviously shows that LDA with SVM achieved the near perfect performance compared with the LDA with ELM. Seen from "green and blue bar" of Fig.5, PCA with ELM obtains better performance than PCA with SVM except the Dentr's FV of HMDB51 and HOF's FV of KTH. Interestingly, ignoring the special case such as Dentr's FV of HMDB51, it obviously shows that PCA with SVM has the worst result while PCA with ELM has the best performance in terms of mAP and time. In addition, LDA with ELM is equal to LDA with SVM. From the experiments, it can be seen that LDA can save more memory space and classify faster than PCA, shown in table 7. In table 7, since ELM is faster than SVM, it's not obvious for PCA and LDA in terms of times. Therefore, we use SVM's time to compare. In addition, HMDB51 is used to compare the efficiency of LDA and PCA as it is more obvious for time. Table 7 shows

280 that LDA is 1000 times faster than PCA in training and 100 times faster in testing.

4.3. The performance of different fusion methods

In this section, we mainly analyze the impact of different fusion methods. Table 1-4 demonstrate that place1 fusion can slightly improve the performance in KTH, while the performance of other datasets is slightly weaker than place2 fusion and place3 fusion. In addition, the recognition rate of HMDB51 degrades significantly in place1 fusion. The reason is that, the classifier will be overfitting by combining different local descriptors of improved dense trajectories. Because the performance of place1 fusion with IDT-MB [41] is slightly improved compare to single descriptor. As shown table 2-4, place2 fusion significantly improves mAP, especially in the case of ELM with PCA. Table 1 shows that place2 fusion has no influence on KTH which is because of the good performance of single descriptor in KTH. It shows that the sum and product of place3 fusion has the best performance compared to other rules with SVM in table 1. In addition, in the case of ELM with PCA, most rules of place3 fusion have similar performance except for the product rule, which has the worst result in table 1 and table 2. There is no absolute advantage of any fusion methods in different datasets. For KTH, the different fusion methods have the similar performance, the place3 fusion gives the best performance in UCF11 with ELM, i.e., 92.51%, while the best result is obtained in HMDB51 and UCF101 with place2 fusion of ELM which is 56.47% and 84.77%, respectively. However, comparing to those tables, it can be seen that place2 fusion is more stable or better than others fusion methods in large-scale complex realistic datasets.

4.4. The performance of different learning methods

305 By comparing the table 1 of learning methods, it shows that SVM is better than that ELM for all kinds of situations in KTH dataset. By analyzing table 2, it indicates that ELM is more comparable to or better than SVM in UCF11. The best mAP of ELM is up to 1% which is better than SVM. What's more,

ELM saves a lot of time due to that it does not needs to be tuned parameters,
 310 shown table 8. From table 3 of HMDB51 and table 4 of UCF101, it can be seen
 that ELM is better than SVM except the case of the descriptor adopt LDA.
 Therefore, in the future, we will adopt PCA with ELM in the realistic large-
 scale dataset. The performance of ELM outperforms SVM in realistic dataset
 that maybe due to the better performance of ELM than other conventional
 315 learning algorithm with higher noise[42]. It is reasonable that the results of
 LDA with ELM are inferior to PCA with ELM for large-scale complex realistic
 datasets, that is due to the number of features of those datasets is relatively low
 with respect to the size of large training sets. It can be seen that ELM of PCA
 in terms of times is comparable to the case of LDA (see the column of table 8).
 320 They are all efficient compared to the SVM.

Fig.6-8 show the best confusion matrix of recognition accuracy for KTH,
 UCF11, and HMDB51 respectively. Seen from Fig.6, it can be observed that the
 actions of boxing, handclapping, jogging, and walking can all be identified and
 the average recognition accuracy is 97.22% which is a sufficiently high accuracy
 325 on KTH. It is obvious that handwaving is confused with handclapping and
 running while being confused with jogging. Therefore, it can be found that the
 fast action is confused with the slow one. In Fig.7 it can be observed that the
 average recognition accuracy is 92.51% which is comparable to the state-of-the-
 art. And we can observe that the recognition accuracy of each action is over
 330 85% except the action of basketball shooting and tennis swinging. They are
 confused with each other. In the future, we will consider how to distinguish the
 basketball shooting and tennis swinging.

Fig.8 shows the best confusion matrix of heat map of HMDB51. Numbers
 are not clear. The color legend is drawn at the right (please view in color).
 335 Table 5 and Fig.9 show the per-class accuracy in more detail and the label is
 marked in table 5. It shows that the per-accuracy of pick, smile, swing baseball,
 sword exercise, throw and wave are all less than 20%. Smile is confused with
 chew, laugh and talk. It is obvious to show that actions are confused with
 each other which being in the same group. Sword exercise is most confused

340 with draw sword and throw is confused with kick ball. Table 5 and Fig.9 also shows that the most low accuracy situation is the type of body movements with object interaction. In the future, we will consider how to distinguish the actions which are in the same group and explore how to distinguish the action of body movements with object interaction. In the subsection, we will compare our best
345 results to the state-of-the-art.

4.5. Compare to the stat-of-the-art

In order to quantify the effectiveness of the method, the obtained results are compared qualitatively with those obtained by other best known state-of-the-art methods (shown table 9). It shows that our descriptor has a classification
350 accuracy of 97.22%, which is comparable to the state of the art. As far as we know, the best accuracy for KTH is 98.2% which is obtained by a high-level representation [43] and it requires non-trivial amounts of hand-labeled training data per each semantic entity (object, part, attribute, etc). Therefore, our method is the best one for the low-level representation on KTH dataset. For
355 a fair comparison, we list Peng et al.[44]’s mAP with traditional FV and stacked FV, respectively. What’s more, Wang et al.[3]’s mAP is separately listed with\without human detection (HD). Table 9 can be seen that on the UCF11 dataset, our method improved by 2% with the same extracting features method, without preprocessing (e.g. HD). The best result of UCF101 is 84.77% which
360 is better than IDT[45], i.e.,84.734% in the first split. We achieve similar performance on HMDB51 with the same condition while our method demonstrate the efficiency. A recent improvement [46] to 63.7% and [44] to 66.79% that rely on extracting FV many times for one video on HMDB51 and sacrifice the time and memory space.

365 5. Conclusion

This paper is to evaluate the effects of dimensionality reduction, fusion methods and learning methods for human action recognition. We find that PCA with

Figure 6: The best confusion matrix for KTH

Figure 7: The best confusion matrix for UCF11

ELM has a better result and the place2 fusion has a stable or better result compared to place1 and place3 fusion. While SVM has no obvious character about which dimensionality reduction techniques should be used with 100% power rate. In future work is to learn which power rate is best for recognition rate. We also analyze the cost of the training time and testing time. It shows that our method can improve accuracy and compute efficiency. Finally, we achieve the state-of-the-art results on UCF11 and HMDB51 datasets by applying our best configuration with the same conditions.

Figure 8: The heat map of best confusion matrix for HMDB51

Figure 9: The bar figure of per class mAP for HMDB51

Table 5: Per class (sorted) mAP for HMDB51

1:brush_hair 86.67%	14:fencing 58.89%	27:pullup 94.44%	40: smile 17.78%
2:cartwheel 61.11%	15:flic_flac 75.56%	28:punch 32.22%	41:smoke 48.89%
3:catch 66.67%	16:golf 96.67%	29:push 56.67%	42:somesault 52.22%
4:chew 70.00%	17:handstand 64.44%	30:pushup 82.22%	43:stand 64.44%
5:clap 73.33%	18:hit 23.33%	31:ride_bike 71.11%	44:swing_baseball 5.56%
6:climb 63.33%	19:hug 80.00%	32:ride_horse 67.78%	45:sword_exercise 18.89%
7:climb_stairs 64.44%	20:jump 44.44%	33:run 45.56%	46:sword 28.89%
8:dive 50.00%	21:kick_ball 48.89%	34:shake_hands 61.11%	47:talk 64.44%
9:draw_sword 41.11%	22:kick 26.67%	35:shoot_ball 75.56%	48:throw 3.33%
10:dribble 85.56 %	23:kiss 78.89%	36:shoot_bow 77.78%	49:turn 62.22%
11:drink 66.67%	24:laugh 68.89%	37:shoot_gun 45.56%	50:walk 52.22%
12:eat 52.22%	25:pick 15.56%	38:sit 78.89%	51:wave 10.00%
13:fall_floor 53.33%	26:pour 75.56%	39:situp 70.00%	

Table 6: pca\lda and non_pca comparison in terms of time for SVM on UCF11

	LDA		PCA		non_PCA	
descriptor	tr_time(s)	te_time(s)	tr_time(s)	te_time(s)	tr_time(s)	te_time(s)
Dentr	0.0500	0.0759	14.2178	0.4320	151.0652	1.9528
HOF	0.0494	0.1359	15.4737	0.5786	522.8764	4.1085
HOG	0.0535	0.0715	16.9994	0.9035	584.5440	4.9395
MBH	0.0630	0.0161	16.3682	0.5582	1314.2	10.8843

Table 7: LDA and PCA comparison in terms of time with the place2 fusion for SVM on HMDB51

	PCA(s)	LDA(s)
training time	787.79	0.78
testing time	32.86	0.33

Table 8: ELM and SVM comparison in terms of time with the place1 fusion on HMDB51

		SVM(s)	ELM(s)
PCA	training time	415.17	2.69
	testing time	34.09	1.37
LDA	training time	8.26	0.85
	testing time	1.67	0.071

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Table 9: Comparison of our method with state-of-the-art methods in the literature

datasets	methods	recognition rate
KTH	Sadanand et al.[43]	98.2%
	<i>ourmethod</i>	97.22%
	Wang et al.[4]	95.0%
	Wu et al.[38]	94.5%
	Bilinski et al.[47]	96.16%
	Wang et al.[48]	93.3%
UCF11	Peng et al. [44] (stacked FV)	93.38%
	<i>ourmethod</i>	92.51%
	Wang et al. [4]	85.4%
	Peng et al. [44]	90.69%
	Zhe et al. [49]	89.4%
	Sapienza et al.[50]	87.2%
	Liu et al.[40]	71.2%
HMDB51	Fernando et al. [46] (VideoDarwin)	63.7%
	Peng et al. [44] (stacked FV)	66.79%
	Wang et al. [3] (HD)	57.2%
	<i>ourmethod</i>	56.47%
	Wang et al. [4]	48.3%
	Wang et al. [3]	55.9%
	Zhe et al. [49]	54%
	Sapienza et al.[50]	40.7%
	Wang et al.[48]	42.1%

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