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A survey on aggregating methods for action recognition with dense trajectories

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Abstract Action recognition has become a very important topic in computer vision with unconstrained video sequences. There are varieties of approaches to feature extraction and video sequences description, which play important roles in action recognition. In this paper, we survey the main representations along dense trajectories and aggregating methods for the videos in the last decade. We mainly discuss the aggregating methods which are bag of words (BOW), fisher vector (FV) and vector of locally aggregated descriptors (VLAD). Furthermore, the newest mean average precision (mAP) obtained from the references is used to discuss different aggregating methods on realistic datasets. And for more intuitive comparison those aggregating methods, we will evaluate them on KTH in the same conditions. Finally, we analyze and compare those papers' experimental data to summarize the trends. Based on the reviews from several approaches to action recognition, we further make an analysis and discussion on the technical trends in this field.

Keywords Action recognition · Aggregating methods · BOW · FV · VLAD · Low-level representation

1 Introduction

Recognizing actions "in the wild" has been an active research topic in computer vision. Here, a video "in the wild" refers to a video captured under uncontrolled conditions from YouTube, movies, etc.. What's more, recognizing actions in realistic settings has caught great attention of researchers from real-time video surveillance and security monitoring, automatic video indexing, and human-computer interfaces [10, 16, 37, 55]. Meanwhile, the problem of recognizing actions in videos is challenging, and all difficulties associated with object detection and recognition task, such as large intra-class variations, partial occlusions, low resolution, camera motion, view point changes, geometric and photometric variances and cluttered background, may also be encountered in action recognition. Therefore, decomposition and

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estimate camera motion, which are based on low rank optimization and features match, are used to modify camera motion [51, 57]. In addition, Kim et.al [20] proposed a method to recognize human actions in arbitrary views by developing 4D space-time features. And Ramanathan et.al [40] provided an overview of the existing methods based on their ability to handle these challenges.

There have been a lot of realistic video datasets proposed for action recognition in the past 5 years, such as Hollywood2 [31], UCF YouTube [29], Olympic [35], UCF50 [41], and HMDB51 [23], UCF sports [43], UCF101 [49], etc.. Some key challenges exist in those datasets, like variation in camera viewpoint and motion, the cluttered background, changes in the position, scale, appearances of the actors, and the large intra-class variation, etc.. Some of them are large-scale datasets which is a large video database such as UCF50, UCF101 and HMDB51 [23, 34], and they are very valuable for evaluating the approaches in real-world action recognition dataset with a large number of classes.

In general, action recognition includes three modules, the feature extraction and description module (the feature module), the video description module, and classification module. The input of the video description module is the feature vectors from the feature module and the output of video description module is video-level descriptor (i.e., mid-level representation or video-level vector) which is obtained by clustering. The input of classification module is video-level descriptor which is more discriminative and compact than feature vector (see Fig. 1). In this survey, we concentrate on the recent techniques which are used for recognizing the realistic action recognition that can obtain the state-of-the-art results. Those techniques include feature extraction, clustering methods and their corresponding classification methods. We focus on feature extraction and description which around dense trajectories such as HOG (histogram of oriented gradients), HOF (histograms of optical flow), MBH (motion boundary histogram), etc.. Dense samples are more prospering compared with sparse interest points [54] and its dense features perform is convinced to have a better performance for complex videos [12, 36, 56]. Meanwhile, we also discuss the popular clustering methods which are bag of words (BOW) [27, 53], fisher vector (FV) [2, 39, 51, 63] and vector of locally aggregated

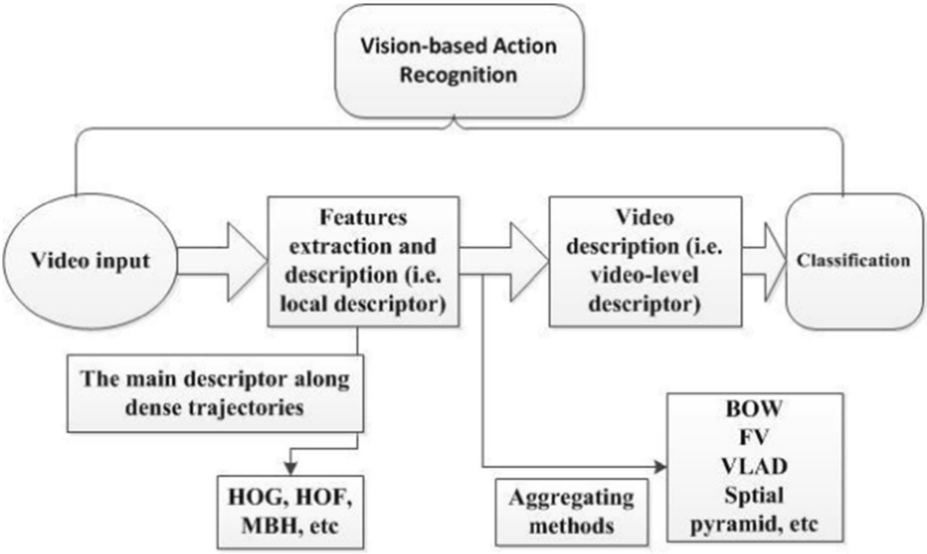
Vision-based Action Recognition
Video input
Features extraction and description (i.e. local descriptor)
Video description (i.e. video-level descriptor)
Classification
The main descriptor along dense trajectories
HOG, HOF, MBH, etc
Aggregating methods
BOW
FV
VLAD
Sptial pyramid, etc

Fig. 1 The action recognition pipeline

descriptors (VLAD) [17–19]. References [6, 24, 27, 54] indicate that BOW was popularly used for action recognition in the past. In addition, Wang [51] evaluated that FV or VLAD can get better performance than BOW for action recognition in realistic videos. Classifier mainly uses $\chi 2$ kernel or linear support vector machine (SVM) for different vector-level representations. In the subsection, we will discuss the popular aggregating methods for action recognition with unconstrained videos.

For the low-level (i.e., features vector or local descriptor), it is very difficult to distinguish the important parts of the representation, and decide which part could be ignored safely. Algorithms which are based on low-level features are not robust enough to complex environment [25, 28] (e.g., cluttered background, camera movements and illumination changes). Therefore, mid-level representation (i.e., video/image-level representation) [3, 5, 11] was proposed in recent years.

Mid-level representation [3, 5, 11, 65, 66] is more compact, flexible, and adaptable than the low-level one. A lot of researchers have been done to figure out the methods to extract the mid-level features. For instance, a novel pooling method of bag of features (BOF) was proposed by Ballas et al. [3] to improve robustness of action recognition. Fathi et al. [11] and zhang et al. [65, 66] extracted mid-level features based on the Adaboost algorithm. Boureau, et al. [5] used the bag-of-word to form mid-level vectors, etc..

Mid-level representation is generally considered to be a suitable classifier input for to reduce computational cost. How to choose different classifiers for various kinds of mid-level vectors? Generally, BOW adopts non-linear SVM which is χ^2 kernel SVM normally. While the FV and VLAD adopt linear SVM. Sometimes, the classification method is designed to be more suitable for the mid-level vector to improve the performance such as [3, 60].

This paper is organized as following: The core techniques of low-level representation around dense trajectories will be briefly discussed in section II. We introduce these different aggregate methods and discuss the newest (i.e., the state-of-the-art) mean average precision (mAP) [3, 8, 32, 33, 51] of datasets for realistic video sequences under these different aggregate methods in section III. The evaluation conditions, datasets and classification methods are listed in section IV, and we also summarize the newest mAP for all kinds of realistic videos with the different aggregating methods and compare different combination, fusion position, and normalization methods with those aggregating methods. We also evaluate the different aggregate methods on KTH dataset for action recognition in this section. Finally, we discuss the technique trends of future researches and conclusions in section V.

In this paper, we denote that because of the polysemous nature of the words, adopting the same terminologies in the research community is an impossible objective to achieve. Such as mid-level representation has the same meaning with video-level descriptor and BOW equals to BOF in this paper.

2 The methods of low-level representation along dense trajectories

In this section, we discuss the key technique of dense trajectories in the low-level in recent years. Dense trajectories were first proposed by Wang et.al [53] which was inspired by dense sampling. Because dense sampling has shown to improve results over sparse interest points for image classification [12, 36]. And for action recognition, dense sampling at regular positions in space and time outperforms state-of-the-art spatio-temporal interest point detectors [54]. In Wang's paper they extracted four descriptors which are HOG, HOF, MBH and trajectory (for convenience, we call it Dentr), respectively and used early fusion [48] to combine them. Among which, HOG, HOF and MBH are extracted along trajectory not around the interest points such as 3D-SIFT [46], HOG3D [21], etc.. In particular, HOG descriptor characterizes static appearance, while HOF and MBH descriptors capture dynamic motion. What's more, HOF captures the local motion information and MBH captures the relative motion information. For realistic videos, they are often complemental to each other, which motivate researchers to fuse these descriptors each other to enhance the discriminative power. They evaluated those video descriptions with bag-of-features approach and have obtained a significant improvement over the state of the art on four datasets which are KTH, YouTube, Hollywood2 and UCF sports, respectively.

However, as the information about clutter motions, such as background changes and camera motions were accumulated, this kind of information was not useful and reduces discriminative power. Hence, the dense sampling was convinced to be not efficient. In the view of above problem, Murthy et al. [33] proposed a technique which selected only a few dense trajectories and then generated a new set of trajectories termed 'ordered trajectories', and the ordered trajectories were about 50 % of the actual dense trajectories amount in [53]. Cho et al. [8] robustly identified local motions of interest in an unsupervised manner and used a multiple kernel method to improve the action recognition performance. Table 1 calculates an average selection ratio (ASR) of the number of selected local motion descriptors (LMDs) to the number of full motion descriptor (FMDs) obtained from each video [8]. It shows that local motion selection method selects only a small fraction of descriptors. From Table 2, it shows that even though ordered trajectories and LMDs [8, 33] can reduce trajectories, the performance of benchmark datasets have slightly improved.

Ballas et al. [3] introduced a new space-time invariant pooling scheme with dense trajectories to improve the performance. It shows that the pooling method has a better performance than the 'ordered trajectories' and LMDs (Table 2).

From Table 2, we can find that dense trajectories can get the best results for different of datasets. However, it is obvious to show that there is still room for the improvement especially in Hollywood2 and HMDB51 which are the real-world actions. What can we do to improve the performance for unconstrained videos? Wang et al. [51] considered the influence of camera motion. They aimed to estimate camera motion and then removed it from dense trajectories. From Table 3, it shows that camera motion has a slightly influence on performance. Improved trajectories obtain a gain of performance of respectively 3, 3 and 2 % for Hollywood2, HMDB51 and UCF50 while Ballas' scheme has 9 and 5 % increase for UCF50 and HMDB51. It inspires us to explore video-level module that can improve the performance for unconstrained videos.

In the next section, we will discuss different kinds of aggregate methods in video-level module for action recognition in recent years.

Table 1 Statistics of selected local motion descriptors. The table is obtain from [8]

	No. of LMDs	No. of FMDs	ASR
Hollywood2	7,717,375	41,183,453	21.8 %
Olympic Sports	2,349,940	15,705,422	21.6 %
UCF11	2,524,486	14,976,537	26.9 %
UCF Sports	470,461	1,998,232	32.2 %
KTH	396,408	1,062,059	40.4 %

Table 2 Reduce trajectory method comparison of different datasets, the mean average accuracy are listed in the table

Methods	KTH (%)	Hollywood2 (%)	UCF sports (%)	UCF 50 (%)	HMDB 51 (%)
Wang et al. [53]	94.2	58.3	88.2	84.5	46.6
Murthy et al. [33]	NA	NA	NA	85.5	47.3
Cho et al. [8]	94.2	60.5	90.3	NA	NA
Ballas et al. [3]	94.6	NA	NA	94.1	51.8

3 The techniques of generate video-level vector

How to bridge semantic gap between low-level features and high-level action categories [44] is a key problem in action recognition. Mid-level representation is more compact and efficient than the low-level representation from previous paper [30].

In general, building a mid-level vector from local features can be broken down into two seeps 1) local features coding and 2) local features pooling (see Fig. 2). There are many coding methods for image classification such as super-vector [7, 67, 68], K-means, OMP-M, Triangle coding and soft thresholding, etc. [22] and polling methods are max pooling and average pooling.

Mid-level features perform a point-wise transformation of the descriptors into a representation adapted to the task. Boureau et al. [5] used the bag-of-words (BoWs) as the mid-level representation. From low-level presentation to mid-level, it focuses on two types of modules which are coding and pooling. Koniusz et al. [22] reviewed a number of techniques for generating mid-level features, including two variants of soft assignment, locality-constrained linear coding, and sparse coding. The pooling methods are divided into average pooling and max pooling. In [5], it is shown that hard quantization is better than soft quantization, and sparse coding is better than soft quantization; max pooling is always superior to average pooling, especially when using a linear SVM; the intersection kernel SVM performed similarly to or better than the linear SVM.

To our knowledge, BOW was widely used for action recognition in last decades. And FV and VLAD were used for action recognition in the past 2 years [2, 17, 18, 33, 51]. In the past, FV was popular in image categorization [38]. The fisher vector extended the BOW by encoding high-order statistics (first and, optionally, second order). VLAD was first proposed by Jegou et al. [19] for image search.

Tombnes's blog [15] indicated that mid-level representation was one of the three trends in computer vision research areas by analyzing paper of CVPR 2013. Therefore, mid-level representation (video-level vector) plays an important role in action recognition. In the subsection we will discuss techniques that are used to achieve mid-level representation.

For image or video vector representation, there are three vector aggregation methods frequently used in action recognition which are BOW, FV, VLAD, respectively. All these

Table 3 Improve trajectory method comparison of different datasets (for [51], list the performance without human detection), the mean average accuracy are listed in the table

Methods	Hollywood2 (%)	HMDB51 (%)	UCF50 (%)
Wang et al. [53]	60.1	52.2	88.6
Wang et al. [51]	63.0	55.9	90.5

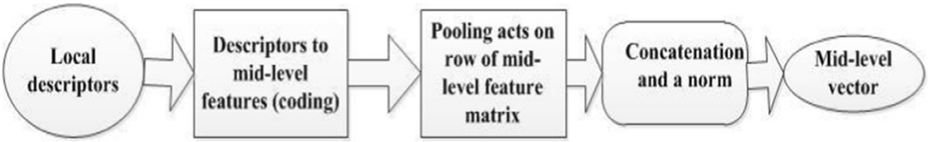
Local descriptors
Descriptors to mid-level features (coding)
Pooling acts on row of mid-level feature matrix
Concatenation and a norm
Mid-level vector

Fig. 2 The typical data-flow for generates a video-level vector which reference [22]

methods are aimed at aggregating d-dimensional local descriptors into a single vector representation which represents an image or a video (see Fig. 2). We will discuss them in the subsection, respectively.

A. Bag-of-words

BOW is the first widely used method for action recognition [8, 14, 23, 24, 27, 29, 31, 41, 44, 50, 52–54, 59]. The BOW representation is the histogram of the number of video descriptors assigned to each visual word. Therefore, the dimension of video vector is equal to the number of visual words. The visual words usually obtained by k-means clustering. Hence, BOW is a hard assignment (HA) or hard quantization (see Eq. (1)). The quantization error may be propagated to the spatio-temporal context features and may degrade the final recognition performance. For classification, χ^2 kernel SVM is usually used to classify the BOW representation.

For action recognition, BOW's simplest form employs HA to solve the following optimization problem:

$$\begin{aligned} &\alpha = \mathrm{argmin}_{\overline{\alpha}} \|X - M\overline{\alpha}\|_2^2 \\ &\mathrm{s.t.} \|\overline{\alpha}\|_1 = 1, \overline{\alpha} \in \{0,1\}^K \end{aligned} \quad (1)$$

In practice, Eq. (1) means that a dictionary M has been formed by k-means clustering, every descriptor X is assigned to its nearest cluster with activation equal one. The L1-norm constraint $\|\overline{\alpha}\|_1 = 1$ ensures that α is histograms. Since α can take only binary values, the L1-norm also ensures a single non-zero entry per α. Equation (1) shows that BOW has high quantisation error. Hence, there are two soft assignment methods popular used for action recognition which are FV and VLAD.

B. Fisher vector

The Fisher kernel (FK) is a generic framework which combines the benefits of generative and discriminative approaches. Perronnin et al. [39] showed that they can boost the accuracy of the FK for large scale image classification. And fisher vector only needs to use linear SVM whose training cost is O(N)-where N is the number of training images. While non-linear SVMs' training time are between O(N^2) and O(N^3). From [53], it is shown that BOW is not suitable for linear SVM. Hence, FV is faster than BOW's classification. In recent years, FV was used for action recognition [32, 51]. Paper [51]'s results shows that FV has a better performance than BOW. In addition, Murthy et al. [32] proposed a technique that combines ordered trajectories' [33] FV with improved trajectories' [51] FV to improve performance.

The FV is an image/video representation obtained by pooling local image/video features. It is frequently used as a global image/video descriptor in visual classification or action recognition.

While the FV can be derived as a special, approximate, and improved case of the general Fisher Kernel framework, it is easy to describe directly. Set v=(X_1,…,X_N) to be a series of D dimensional features vectors (e.g., HOG, HOF, MBH), which are extracted from an image/video. Set $\Theta=(\mu_k, \Sigma_k, \Pi_k : k=1,\ldots,K)$ to be the parameters of a Gaussian Mixture Model (GMM) to fit the distribution of descriptors. The GMM associates each vector X_i to a mode k in the mixture with a strength given by the posterior probability:

$$q_{ik} = \frac{(X_i - \mu_k)^T \Sigma_k^{-1} (X_i - \mu_k)}{\Sigma_{t=1}^{K} (X_i - \mu_t)^T \Sigma_t^{-1} (X_i - \mu_t)}$$

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

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

where $j=1,2,\ldots$,D spans the vector dimensions. The FV of image/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:

$$\Phi(V) = [\cdots u_k \cdots v_k \cdots]^T$$

where $[\cdot]^T$ means the transpose of vector. Hence, each video is represented by a 2DK dimensional FV for each descriptor type.

The FV representation has many advantages w.r.t the BOW. Firstly, it provides a more general way to define a kernel from a generative process of the data: we show that the BOW is a particular case of the FV where the gradient computation is restricted to the mixture weight parameter of the GMM. From paper [32, 51] it is shown that the additional gradients incorporated in the FV bring large improvements in terms of accuracy. Secondly, it can be computed from a much smaller number of centroids in terms of mAP (e.g., a 4000 visual word BOW is comparable to a 256 centroids FV or VALD [9, 17, 33, 51]). Thirdly, even with simple linear classifiers, it can still perform well. A significant benefit of linear classifiers is that they are very efficient to evaluate and computationally economical to learn.

C. Vector of locally aggregated descriptors

VLAD is a simplified non-probabilistic version of FV which is an extremal case of FV. VLAD was first proposed by Jegou et al. [19] for image search. It shows that VLAD achieved a significant outperforms improvement than ever before, and it is more efficient than BOW. In recent years, VLAD was first used for action recognition [17, 33], and it is efficient for its effectiveness compared with a non-linear kernel and post-processed using a component-wise power normalization and L2-normalized (i.e., referred to as SSR), which dramatically improves its performance [17, 33]. Ordered trajectories' [33] results are 1.9 % (absolute), which is better than paper [17] for HMDB51 dataset.

VLAD is a feature encoding and pooling method, and similar to FV. VLAD encodes a set of local features descriptors V=(V_1,…V_N) extracted from an image/video using a dictionary built based on clustering method such as GMM or K-means clustering. Set q_{ik} to be the strength of the association of data vector x_i to cluster μ_k, such that and the association may be either soft (e.g., obtained as the posterior probabilities of the μ_k are the cluster means, vectors of the same dimension as the data V_i. VLAD encodes feature V by considering the residuals)

$$v_k = \sum_{i=1}^{N} q_{ik}(V_i - \mu_k)$$

The residuals are stacked together to obtain the vector

$$\Phi(V) = [\cdots v_k \cdots]^T$$

where $[\cdot]^T$ means the transpose of vector. Therefore, each video is represented by a DK dimensional VLAD for each descriptor type. There are three normalized methods for VLAD which are component-wise L2 normalization, square-root and L2 normalization, as well as Component-wise mass normalization. Component-wise mass normalization which is called NormalizeMass corresponding to each vector v_k is divided by the total mass of features. Square-rooting and L2-normalization [39] which is called SSR corresponding to each $\Phi(V){:=}sign(\Phi(V))|\Phi(V)|^{\alpha}$ and $\Phi(V) := \frac{\Phi(V)}{\|\Phi(V)\|_2}$. Component-wise L2 normalization which is called NormalizeComponents [1, 9] corresponding to the vector v_k divided by their norm $\|v_k\|_2$. We will evaluate the three normalized methods in the next section.

In the next section, we will introduce experimental conditions, then discuss and summarize the three aggregating methods, respectively.

4 Analysis and comparison of the experiment data

In this section, we first introduce the datasets, corresponding experimental conditions and classification methods used for action recognition in the references. Then the mean average precision (mAP) is listed for all datasets in the subsection of this paper. In recent years researchers proposed the realistic datasets for research such as Hollywood2 [31], UCF sports [43], Olympic [35], UCF50 [41], HMDB51 [23], UCF101 [49] etc.. UCF50, UCF101 and HMDB51 are large datasets which are more complex compared to Hollywood2. Table 4 shows the list of action datasets.

Table 4 Action datasets

Datasets	Number of actions	Camera motion	Background
KTH [45]	6	slight motion	static
UCF Sports [43]	10	present	dynamic
Olympic Sports [35]	16	present	dynamic
HOHA [31]	12	present	dynamic
UCF101 [49]	101	present	dynamic
UCF50 [41]	50	present	dynamic
HMDB51 [23]	51(47)	present	dynamic

A. Datasets

KTH [45] composes of 6 classes of 25 human actions. The videos are subject to different zoom rates and have mostly non-cluttered static backgrounds. The evaluation listed in this paper all uses the training/testing division of Schuldt [45].

UCF sports [43] contain ten human actions. The video shows a large intra-class variability. Wang et al. [51] and Cho et al. [8] used a leave-one-out setup and test on each original sequence while training on all other sequences together with their flipped versions.

Olympic Sports [35] has 16 sports actions which consist of athletes practicing different sports. All experiments use 649 sequences for training and 134 sequences for test in our paper.

Hollywood2 (HOHA) [31] contains 12 action classes which are collected from 69 different Hollywood movies. It contains 1707 video split into a training set (823 videos) and a test set (884 videos). Training and test videos come from different movies.

UCF101 [49] has 101 action categories which are classified into 25 groups. From which, Clips of 7 groups are used as test samples and the remains for training.

UCF50 [41] has 50 action categories taken from YouTube. For all 50 categories, the videos are split into 25 groups or 5 groups. Wang et al. [16, 52] and Murthy [33] applied the leave-one-group-out cross-validation to 25 groups. While Ballas et al. [3] used 5 folds leave-one-out group-wise cross validation which is listed in Table 2.

HMDB51 [23] is composed of 6849 videos clips divided into 51 action categories. The different actions have large appearance variation. It all adopts the default training and testing splits [23].

B. Classification method

In general, to classify action recognition of BOW histograms under unconstrained videos, it usually uses a non-linear SVM with a multi-channel χ^2 kernel [23, 27, 31, 53], etc.. We use the multi-channel Gaussian kernel defined by:

$$K(H_i, H_j) = \exp\left(-\sum_{c \in C} \frac{1}{A_c} D_c(H_i, H_j)\right)$$

where $H_i=\{h_{in}\}$ and $H_j=\{h_{jn}\}$ are the histograms for channel c and $D_c(H_i,H_j)$ is the $\chi 2$ distance defined as

$$D_c(H_i, H_j) = \frac{1}{2} \sum_{n=1}^{V} \frac{(h_{in} - h_{jn})^2}{h_{in} + h_{jn}}$$

where V is the vocabulary size. The parameter A_c is the mean value of the distances between all training samples for channel c [64]. While Adaboost with C.45 may be used to classify the histogram of BOW for action recognition [29].

For FV and VLAD, the linear classifier will be used to classify them with the advantage of low cost [17, 32, 39, 51]. In our experiment, C is set to be 100 for linear SVM, which has been shown to obtain good results when validating on a subset of training samples.

For the tables in this paper, we should note that we list the best results obtained from their corresponding papers, and the performance is measured by mAP over all classes.

C. Evaluation of these aggregation methods

From the above paragraphs, it is shown that FV and VLAD have freshly been used for the application of large-scale action recognition since 2013. In the future we have to explore how to make full use of them. From Table 5, it is shown that FV and VLAD work well for large-scale action recognition. What's more, the FV and VLAD significantly outperform BOW for realistic videos. Hence, FV and VLAD will be popularly used for action recognition in the future since they are simple yet effective. What's more, we can design better aggregating methods. For instance, we can design FV or VLAD's normalization method or use dimensionality reduction techniques [61] to improve the accuracy and effectiveness.

From Fig. 2 it is shown that the last step to generate a video-level vector is normalization. Table 6 lists the impact of VLAD normalization methods and the methods of generating VLAD for image retrieval in terms of mAP. It can be seen that VLAD with "innorm" normalization method achieves the best result. It is intuitive to consider how the normalization methods influence the action recognition. Therefore, we will evaluate the impact of normalization method with VLAD on action recognition. For simplicity, we will use KTH with constrained video to evaluate the different normalization methods. Before comparing the different normalization methods, we first evaluate the influence of the number of centroids K on mAP for KTH dataset when using VLAD in Fig. 3. To limit the complexity, we cluster a subset of K multiplying 1000 which is randomly selected training features using k-means. It is shown that the larger the K is, the better the performance will be ($K \leq 150$). Otherwise, the mAP irregularly changes with respect to the K since randomly selected training features using k-means. For the below pyrography, we choose $K=256$ for FV and VLAD, while BOW has 4000 visual words consistent with the literature [51, 53].

Table 7, we compare two different normalization methods for VLAD on KTH with constrained videos. It shows that the NormalizeCompoents plus SSR have a better result than the NormalizeMass plus SSR, and NormalizeComponets outperforms Normalizemass by one percent of mAP. Hence, in the subsection evaluation, we will use NormalizeComponents plus SSR to normalize the vector for VLAD and SSR for FV.

In this section, we will evaluate the combination of descriptors with different aggregating methods. In Table 8 we list different combinations of descriptors with BOW which is obtained from Ref [52]. Table 9 analyze the different combination strategies of FV and VLAD respectively. From those tables, we can see that: in most datasets the more descriptors for combination, the better mAP. While in some special cases, the special combination can achieve the best result such as the KTH in Table 10. For more intuitive comparison, we will evaluate those aggregating methods on KTH.

In Table 10 we evaluate different aggregating methods for KTH dataset and use paper [8] as the baseline. We choose to use one scale for the descriptor of Wang's

Table 5 Aggregate methods comparisons of different datasets (BOW only gives the mAP around trajectories and for [51] list the performance without human detection.)

Dataset	Aggregate method		
	FV (%)	VLAD (%)	BOW (%)
Hollywood2	63.0[51]	62.5[17]	58.3[53]
Olympic sports	90.2[51]	83.2[17]	74.1[52]
UCF50	90.5[51]	NA	84.5[52]
HMDB51	55.9[51]	49.9[33] 52.1[17]	46.6[52]
UCF101	95.44[32]	NA	NA

Table 6 Comparison of different normalization methods on image retrieval with mAP for VLAD (taken from [1])

Method\vocabulary	Ox5k	Paris	Flickr60k
VLAD	0.519	0.508(98 %)	0.315(61 %)
VLAD+SSR	0.546	0.532(97 %)	0.374(68 %)
VLAD+adapt	0.519	0.516(99 %)	0.313(60 %)
VLAD+adapt+SSR	0.546	0.541(99 %)	0.439(80 %)
VLAD+adapt+innorm	0.555	0.555(100 %)	0.478(86 %)

paper [53] which they use eight. For FV and VLAD we set K=256 while K=4000 of BOW. Linear SVM is used for FV and VLAD while SVM with χ^2 kernel is used for BOW. In Table 10 ‘all combine’ means combining HOG, HOF, MBH and Dentr. From Table 10, it is shown that VLAD and BOW obtain the best result which is 96.3 %. We can conclude from the column of FV and BOW that the result degrades when combining all descriptors. Therefore, we still need to optimize the combination of descriptors and design a suitable fusion method for action recognition in the future. Form the row comparison of the table, it is shown that there has not been a method can be certainly determined which aggregating method should be applied for KTH dataset with constrained videos. We will analyze it for large-scale dataset with realistic videos in the future.

5 Future trends and conclusions

Although significant efforts have been devoted to recognize action with realistic setting during the past few years, the current recognition accuracy for large datasets and unconstrained videos

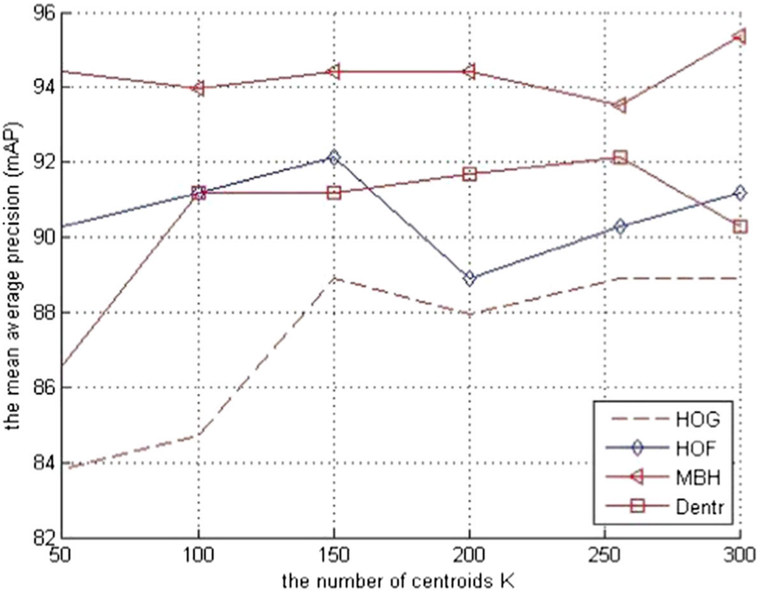

Fig. 3 mAP versus the number of centroids K for VLAD

Table 7 Comparison of different normalized method on KTH with mAP for VLAD (where K=150)

Descriptor	Normalized method	
	NormalizeComponents+SSR (%)	NormalizeMass+SSR (%)
HOG	88.89	87.96
HOF	92.13	90.28
MBH	94.44	93.98
Dentr	91.20	90.28

is still far from satisfaction. In this section, we discuss several promising techniques that may improve action recognition performance significantly. How to improve the mAP for the large datasets in the realistic video sequences which is necessary in the real life applications? In the next part we will give several directions which may be used to improve the mAP.

Explore better feature detector and descriptor There have been many descriptors for action recognition such as 3D-gradient [21], 3D-SIFT [46], etc., and some new descriptors have been proposed in recent years [4, 13, 42, 47, 53, 57]. Some descriptors are along the trajectories, the others are along the interest points (IPs). There are many methods to select or extract IPs. Bilinski et al. [4] proposed a novel figure-centric representation which captured both local density of features and statistics of space-time ordered features. It is novel to consider the space-time order of features. Therefore, it is important to exploit IPs which is representative and discriminative to capture relationships between local features and consider the space-time order of features in the future. Shabani et al. [47] introduced the concept of learning multiple dictionaries of action primitives at different resolutions which they called multiple scale-specific representations. They aimed at exploiting the complementary characteristics of the motions across different scales. Hence, capture complementary information is a trend for all kinds of methods. It is obvious the result from Tables 8, 9, and 10 can improve accuracy when combining with some complementary descriptors.

Design fusion There have been numerous work for feature fusion [6, 26, 28, 31, 48, 58, 62]. For early and late fusion, they only consider the scenes in the well-constrained condition. From the prior work, it shows that early fusion can more efficiently capture the relationship among features yet it is prone to over-fit the training data. Late fusion deals with the over-fitting problem better but does not allow classifiers to train on all the data at the same time. Hence, double fusion which simply combines early fusion and late fusion together to incorporate their advantages in [59]. The future work will focus on designing a scheme to automatically select and optimize early fusion subset to combine with late fusion and aim at exploring the suitable place to fuse for early fusion. Therefore, it can save storage space and be more efficient.

Table 8 Comparison of different combination of descriptors with mAP for BOW (taken from [52])

Datasets	KTH	Hollywood2	Olympic sports	UCF50	HMDB51
MBH	95.0	55.1	71.6	82.2	43.2
Combined	94.2	58.2	74.1	84.5	46.6
MBH+STP	95.3	57.6	74.9	83.6	45.1
Combined+STP	94.4	59.9	77.2	85.6	48.3

Table 9 Comparison of different combination of descriptors with mAP for FV and VLAD (taken from [7])

Fusion	HMDB51				UCF101			
	FV		VLAD		FV		VLAD	
	d-level	k-level	d-level	k-level	d-level	k-level	d-level	k-level
HOG+MHB	50.9 %	50.4 %	47.0 %	48.5 %	NA	NA	NA	NA
HOG+HOF	47.0 %	48.3 %	44.4 %	47.7 %	76.1 %	77.7 %	75.7 %	77.5 %
MBH(x+y)	49.2 %	49.1 %	45.2 %	47.0 %	78.9 %	78.7 %	75.6 %	76.3 %
Combine	52.4 %	53.2 %	51.5 %	52.6 %	81.1 %	81.9 %	80.6 %	81.0 %

For early fusion, it has two places to fuse, which is in the local descriptor (place1) or in the mid-level vector (place2). The early fusion often is considered in place2 for different kinds of local descriptor [31, 51, 53]. While the spatio-temporal pyramid often fuses in the place1 such as [51, 53], and sometimes in the place2 [1, 61]. Table 9 shows that place2 (k-level) fusion is better than place1 (d-level) fusion in most cases. In the future we will explore which place to fuse for large-scale action recognition.

Design better aggregating method As we know that the FV and VLAD begin to use recognizing action with unconstrained videos in 2013. How to design more compact and discriminative FV and VLAD is important for action recognition. Arandijelovic et al. [1] were through three stages to improve the performance of VLAD which were intra-normalization, multi-VLAD and vocabulary adaptation for image retrieval. Delhumeau et al. [9] were through two aspects to re-visite VLAD which are residual normalization and local coordinate system (LCS) for image classification. There are a few researches for action recognition in this field. Ballas et al. [3] proposed a novel pooling strategy for action recognition, which obtained a significant improvement of 62 % for UCF 50. It is obvious that to design a better pooling or coding method can significantly improve both accuracy and efficiency. Therefore, it is important to design a suitable coding or pooling strategy for action recognition with realistic videos.

In the future our goal is to achieve sparse, fast, efficient and robust algorithm. We can design algorithm from the three points discussed in the above section. Furthermore, they are also the main pursuits in computer vision.

Table 10 Comparison of different aggregating method for KTH dataset with mAP

Descriptor	Aggregate method			Paper [8] as baseline (%)
	FV (%)	VLAD (%)	BOW (%)	
HOG	83.8	88.9	88.4	87.6
HOF	93.5	90.3	93.0	92.7
MBH	92.1	93.5	95.4	94.4
Dentr	91.2	92.1	92.6	88.6
Dentr+MBH	93.5	96.3	96.3	NA
Dentr+MBH+HOF	94.9	96.3	95.8	NA
All combine	94.44	96.3	94.9	94.2

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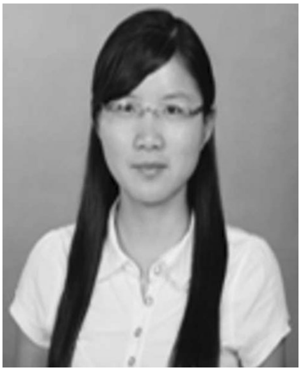

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