Signal Processing 144 (2018) 323–332

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Distinctive action sketch for human action recognition

Ying Zheng[a,b], Hongxun Yao[a,*], Xiaoshuai Sun[a], Sicheng Zhao[c], Fatih Porikli[b]

[a] School of Computer Science and Technology, Harbin Institute of Technology, China
[b] Research School of Engineering, Australian National University, Australia
[c] School of Software, Tsinghua University, China

ARTICLE INFO

Article history:
Received 16 March 2017
Revised 16 October 2017
Accepted 19 October 2017
Available online 20 October 2017

Keywords:
Action sketch
Sketch pooling
Action recognition

ABSTRACT

Recent developments in the field of computer vision have led to a renewed interest in sketch correlated research. There have emerged considerable solid evidence which revealed the significance of sketch. However, there have been few profound discussions on sketch based action analysis so far. In this paper, we propose an approach to discover the most distinctive sketches for action recognition. The action sketches should satisfy two characteristics: sketchability and objectiveness. Primitive sketches are prepared according to the structured forests based fast edge detection. Meanwhile, we take advantage of Faster R-CNN to detect the persons in parallel. On completion of the two stages, the process of distinctive action sketch mining is carried out. After that, we present four kinds of sketch pooling methods to get a uniform representation for action videos. The experimental results show that the proposed method achieves impressive performance against several compared methods on two public datasets.

1. Introduction

With the flourish of computer vision, sketch based technology is becoming a rising star for multitudinous researchers all over the world. It is well acknowledged that sketch has an important practical significance. In the past few years, there have been numerous works tackling sketch related problems from different angles. They mainly focused on three areas, namely sketch based image retrieval [1,2] and composition [3,4], sketch based video retrieval [5,6], sketch segmentation [7,8] and recognition [9,10]. Although it is a widespread idea since the success of sketch based approaches that studying the sketch of visual elements is one of the most fundamental prerequisites for many vision applications, there is still limited studies revolving around action sketch.

We can probably find the trace of action sketch in the system of sketch based video retrieval. But almost all of existing works concentrate on how to create a better algorithm for video clip searching, departed from free-hand sketch queries which depict the shape, color and movement of objects roughly [5]. Unlike any of these sketch based video retrieval works, we do not seek to achieve determinate mapping between input sketch and video. In fact, our problem goes retrograde in some ways, because we want to transform action video into sketch. The progress of this issue be a powerful auxiliary tool for many works, such as action recognition, and retrieval [11,12].

Among these scarce groups associated with action sketch, A.Yilmaz's work [13] is the most similar one to ours. They present a method of action representation on spatio-temporal volume (STV) and differential geometric surface properties. How to represent action better for tasks like action recognition is what they chased. Besides, the first premise they assumed is that object contours for each action slice are given. In contrast, our work principally seeks conversion between action and sketch which is one step ahead of action representation.

In this paper, we propose a method of distinctive action sketch mining for human action recognition. First of all, we generally explore the characteristic of sketch in action and build an applicable system to discover the most distinctive action sketches possessing sketchability and objectiveness. For action videos, sketches of each clip can be well generated in real time. Combining these elaborate sketches, we propose a distinctive ranking method of action sketches. The top ranking sketches can typically represent the action classes which they belong to. Among the obtained top ranking sketches, we introduce an approach of feature pooling to get a new representation for action video. Then the new representation will be combined with local feature based representation such as the improved dense trajectories with Fisher vector encoding. Fig. 1 gives the overview of our method.

The main contributions of this work are summarized in threefold:

* Corresponding author.
E-mail addresses: zhengying@hit.edu.cn (Y. Zheng), h.yao@hit.edu.cn (H. Yao), xiaoshuaisun@hit.edu.cn (X. Sun), zhaosicheng@tsinghua.edu.cn (S. Zhao), fatih.porikli@anu.edu.au (F. Porikli).

https://doi.org/10.1016/j.sigpro.2017.10.022
0165-1684/

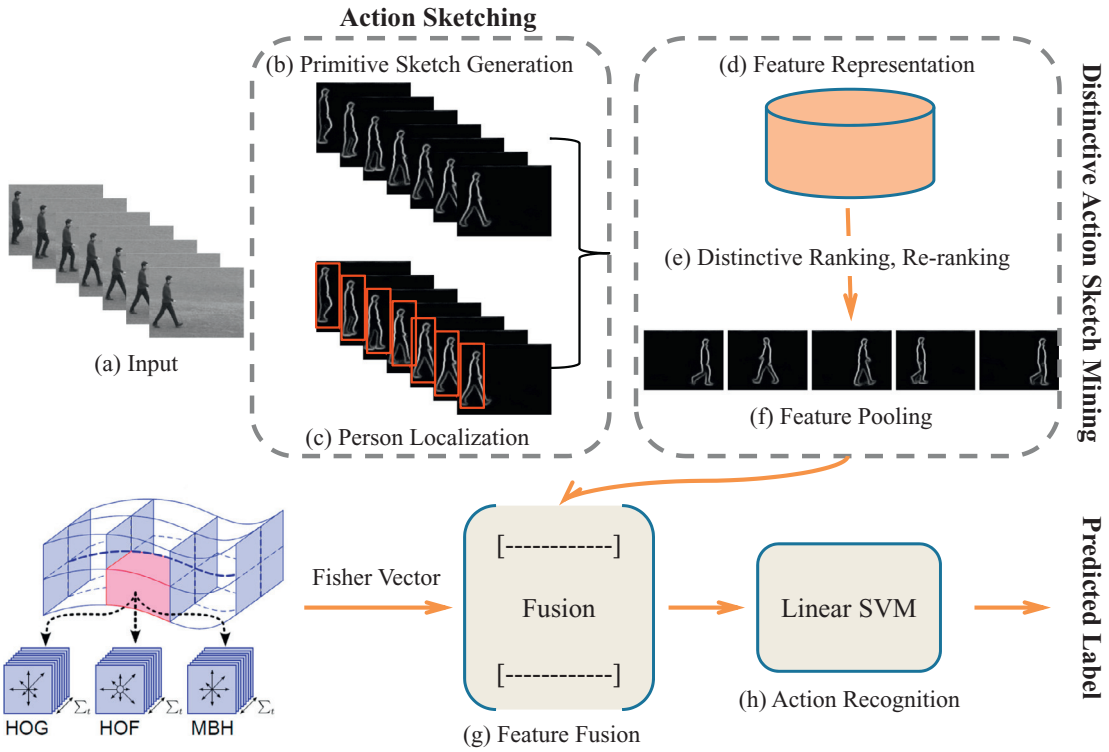


Fig. 1. Overview of our method. (a) Input: action videos. (b) Transform each action frame to primitive sketch in real time by fast edge detection method [14]. (c) Locate person by Faster R-CNN [15]. (d) Represent sketches as feature vectors. (e) Discover the top distinctive action sketches through ranking and re-ranking. (f) Apply feature pooling on the top ranking sketches to get a new representation. (g) Perform representation-level fusion with improved dense trajectories with Fisher vector encoding. (h) Recognize action videos by a linear SVM and choose the prediction with highest score as the predicted label.

- We introduce sketch to the field of action recognition and propose a ranking based method to discover the most distinctive action sketches.
- We present a novel approach of action representation based on four kinds of sketch pooling strategy.
- Extensive experiments on two public human action datasets are conducted to demonstrate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. Section 2 reviews the works related to our research. Section 3 shows how to transform the human action to sketches. Section 4 describes the distinctive ranking method of action sketches. Section 5 introduces the approach of feature pooling for action recognition. Section 6 presents the experimental results, followed by conclusion in Section 7.

2. Related work

As one of the most important research fields in computer vision, human action recognition has a wide range of applications, such as human-computer interaction, video surveillance and robot action control. In the past years, numerous approaches have been proposed to understand and recognize human actions from different angles and levels. Among these works, action representation is a key step towards a good action recognition system [16]. In practice, a human action clip can be represented by different views or features, such as motion, gradients, and shapes. The action sketch we proposed can be seen as one kind of views. In this section, we will give a brief introduction of feature representation for action recognition and several other works closely related to our research. For a wider range of studies on action recognition, we recommend the insightful reviews [11,17,18] to interested readers.

Traditional approaches for action recognition are mainly based on single feature representation, such as local and global feature representation [19–21]. Based on hand-crafted descriptors or neural networks, these methods can achieve good performance. However, the problems of lighting and viewpoint changes, complex backgrounds and intra-class variations have made it very challenging to get a higher accuracy. To address this problem, many researchers propose new representations which combine different features together. In consideration of the particular characteristics possessed by different kind of features, some well-designed combinations are usually superior to the single feature representation. These methods can be classified into two groups, direct catenation [22] and multi-view learning [23–25]. For direct catenation, space-time interest points (STIP) [26] and improved dense trajectories (IDT) [27] are the most classic works. Under the standard bag of visual words (BoVW) framework, Laptev et al. [28] demonstrate the effectiveness of feature combination of the histograms of oriented gradient (HOG) descriptors and histograms of optical flow (HOF) descriptors computed for STIP. For IDT based representation, Wang et al. [27] catenate four descriptors (i.e., trajectory, HOG, HOF and motion boundary histograms (MBH)) coded by Fisher vector and obtain the state-of-the-art performance for action recognition at that time. Different from direct catenation, multi-view learning based methods focus on exploring the relationship between different features [29] and incorporate these heterogeneous feature descriptors into one low-dimensional and compact representation [30]. Although this two kinds of works have explored numerous and diverse features, taking the sketch to represent action is a new and largely unexploited frontier.

An early preliminary version of this work was published in [31]. Compared to the earlier version, the biggest difference is that we propose a novel method of action representation based on sketch pooling. We also replace the person detection method with the

state-of-the-art Faster R-CNN [15]. Furthermore, we present a unified approach for distinctive action sketch mining. Among other related works, silhouette and skeleton are similar to action sketch. The silhouette is usually a black-white image using the edges to draw the outline of person or object. It is a critical research medium in the field of human pose recovery. Typical approaches of image-based pose recovery reconstruct 3D poses by the learned mapping function between 2D silhouettes and 3D poses [32–34]. For human skeleton, it is composed of several rigid segments which are articulated by joints. The skeleton looks like a matchstick man that forms the rough structure of a human body. By modeling and classifying the temporal evolution of human skeleton, human action can be recognized in a 3D feature space [35,36]. Unfortunately, both silhouette and skeleton are mostly applied in 3D video sequences that require a sophisticated motion capture system or effective depth sensors. For this reason, they cannot be implemented to the conventional human action videos while the proposed action sketch does not have this limitation.

3. Action sketching

When we talk about painting art, a sketch usually refers to a quick and informal drawing done from real life. An excellent sketch should capture the essentials of a subject, which may be the overall neurogram and characteristic details from a specific perspective. In a general sense, the only primary mission for static image sketching is to hit the spot of greatest possible similarity of both dominant lines. However, moving to action videos, the situation is quite different in the aspect of object's subjectivity. Meanwhile, it is the key factor we need to consider. We implement appropriate measures to satisfy the requirement in action sketching.

3.1. Primitive sketch generation

In the previous works, Yilmaz et al. take the object contours as their basic elements [13]. Admittedly, object contours may have some certain degree of ability to express the sketch of action. Nonetheless, the ability is not enough to fully appear in the person of action sketch. Beyond that, methods like trackability maps [37] and action templates [38] are also proposed to represent action videos. Leaving aside the performances of these methods, the outcome has identifiable differences as compared with the sketch.

In our research, the primary character for sketching action will be referred to as ***sketchability***. Methods that meet the requirements of sketchability must be able to depict the full profile of subject similar to object contours and some other important details. It should be pointed out that the transformation between real image and sketch is immensely challenging [39]. This is not our work in this paper. A reasonable way is to select some appropriate representative edges for each action clip. To generate the primitive sketch, we adopt the fast edge detection method proposed by P. Dollár et al. [14]. In consideration of the structure underlie local image patches, they presented a structured learning framework for local edge mask prediction integrated into random decision forests. In this stage, we can transform each action frame to primitive sketch in real time.

3.2. Person localization

What we are talking about here is human-centered action videos. Of course, it can be easily extended to other types of subjects. The most important characteristic of these videos is that the actions must be performed by a specific subject. We call this property of action videos ***objectiveness***.

To capture the objectiveness in action videos, we use the method called Faster R-CNN [15] as an accurate and efficient tool for person localization. The Faster R-CNN depends on region proposal network (RPN) that shares full-image convolutional features with the detection network, which makes it become the state-of-the-art object detection network. In practice, we use the open sourced code of Ren et al. [15] and the ImageNet pre-trained network released on their website[1] to detect the person in each frame. Then we filter out the detections with too small size and unsatisfied aspect ratio for better model detection. It is necessary to note that this stage is completely independent of the stage of primitive sketch generation, so we can deal with this two processes in two parallel channels, which can provide significant run time savings. After that, we will get a corresponding sketch which is only associated with the subject for every action clip when combining these two stages together.

4. Distinctive action sketch mining

It is generally known that there are discriminative and representative themes with semantic interpretation in a specific type of photos, such as city and landscape images [40,41]. Similarly, some distinctive patterns also exist in different types of actions. While the actions appear in the form of sketch, distinctive sketches will correspond to these patterns. Acquisition of these sketches can be a significant assistant to many action related applications. In this section, we will present the details of the proposed method for distinctive action sketch mining.

4.1. Feature representation

Given a sequence of action sketches generated in the stage of action sketching, we must first find a fine feature representation for every sketch. It is generally agreed that a deeper convolutional neural network can describe richer semantic information of the image. However, the very deep network calls for large-scale labeled training dataset, which is not always available in research. Fortunately, there are a handful of superior deep models for image classification from ImageNet large scale visual recognition challenge (ILSVRC). These deep nets are delicately designed and well trained with millions of images from ImageNet. Ali et al. [42] report that the pretrained deep model from ILSVRC is able to get consistent superior results on a diverse range of tasks including scene recognition, image retrieval, etc. Notably, the recent work of Sketch-a-Net proposed by Yu et al. [43] present persuasive evidence that deep model is a super choice for representation of sketch. To get better representative features, we employ the VGG-19 Net [44] and extract features of each sketch from the fully-connected (FC) layer. Finally, the sketch will be represented by a feature vector X with 4096 dimensions.

4.2. Distinctive ranking

We want to discover these sketches which can distinctively represent a particular category of action. In other words, these distinctive action sketches have to meet requirements of the following two aspects: a) sketches must be very representative in the class they belong to; b) they also should be diverse among the sketches we selected.

For the first requirement, we propose a distinctive ranking method based on clustering. Among these feature vectors X of sketches, we gather them into k clusters by k-means and get the feature vectors Y of each cluster center. After that, all sketches are

[1] https://github.com/ShaoqingRen/faster_rcnn

ranked according to the distinctive score computed by

$$S = \frac{\sum_{i=1}^{k} d_{12}(X_c, Y_i)}{d_{12}(X_c, Y_s)}, \tag{1}$$

where d_{12} refers to the Euclidean distance, X_c and Y_s are the feature vector of current sketch and the center of its cluster respectively.

In the fraction above, $d_{12}(X_c, Y_s)$ denotes distance between current sketch and its cluster center. A smaller value means that the sketch is more likely to represent the class it belongs to. On the other hand, $\sum_{i=1}^{k} d_{12}(X_c, Y_i)$ indicates the sum of distance from the sketch to every cluster center. A larger value shows that the sketch is more diverse among these sketches. The scores by division between them can trap the degree of distinctive property. What we want is that the most representative sketches have the highest order. It can be represented by a function D of distinctive score maximization, which is formulated as follows,

$$\begin{aligned} D &= \max_{\theta} \sum_{i=1}^{n} (n-i+1) S_{\theta_i} \\ &= \max_{\theta} \left\{ (n+1) \sum_{i=1}^{n} S_{\theta_i} - \sum_{i=1}^{n} i S_{\theta_i} \right\} \end{aligned} \tag{2}$$

where θ is an array with n parameters that indicate the positions to place each sketch, n means the number of sketches in an action clip, and S_{θ_i} denotes the distinctive score of the θ_ith sketch. Only when the value of S_{θ_i} is greater than S_{θ_i+1} $(i = 1, 2, \ldots, n-1)$, the Eq. (2) can get the maximal value. Given the distinctive scores of all sketches computed by Eq. (1), the first item of Eq. (2) equals to a constant C. Hence the equation is converted to

$$\begin{aligned} D &= \max_{\theta} \left\{ C - \sum_{i=1}^{n} i S_{\theta_i} \right\} \\ &= \min_{\theta} \sum_{i=1}^{n} i S_{\theta_i} \end{aligned} \tag{3}$$

Now the maximization function of distinctive score becomes a process to find the arrangement of sketches that can minimize the value of Eq. (3). To achieve this goal, all sketches are ranked in descending order based on the distinctive scores.

4.3. Re-ranking

Distinctive ranking gives us an acceptable mining result of action sketches, but it is coarse somewhat and has a potential shortcoming. From the top row of Fig. 2, we can see an undesired phenomenon that several similar sketches have close order. That is to say, the ranked sketches cannot satisfy the second requirement of distinctive action sketch. In such cases, a sectionalized re-ranking approach is presented to overcome the shortcoming.

In consideration of practical necessity and computation cost, we limit the re-ranking process to a separate interval w of ranking order. When the top m ranking sketches are the expected output, we do re-ranking among double ranking sketches, i.e. the interval w equals $2m$. For example, if we set m as 10, then we only need to do re-ranking on the top 20 distinctive action sketches. At the individual range, we iteratively find the most dissimilar one with sorted sketches in the remaining samples. The procedure can be formalized as:

$$\max_{p} \sum_{k=1}^{j-1} \sqrt{\sum_{t=1}^{d} (x_{pt} - x_{kt})^2}, \tag{4}$$

where $p = \{j, \ldots, w\}$, j marks the current position calling for re-ranking in the process of iteration, d means the dimension of feature vector X. The re-ranking process is designed to maximize the diversity of action sketches obtained in the stage of distinctive ranking. Based on Eq. (4), it can be written as

$$R = \max_{\varphi} \sum_{j=2}^{w} \sum_{k=1}^{j-1} d_{12}(X_{\varphi_j}, X_{\varphi_k}), \tag{5}$$

where φ is a new arrangement for the top w action sketches obtained in the distinctive ranking stage, $d_{12}(X_{\varphi_j}, X_{\varphi_k})$ computes the Euclidean distance between feature vectors of the φ_jth and φ_kth action sketch. By combining Eqs. (3) and (5), the process of distinctive ranking and re-ranking can be unified into a max-min formulation,

$$\max_{\varphi} \min_{\theta} \sum_{i=1}^{n} i S_{\theta_i} + \sum_{j=2}^{w} \sum_{k=1}^{j-1} d_{12}(X_{\varphi_j}, X_{\varphi_k}). \tag{6}$$

Fig. 2 shows an illustration of distinctive action sketch mining. After the operation of re-ranking on the sketches generated above, the discovered action sketches are more distinctive and acceptable.

5. Sketch pooling for action recognition

After obtained the top m distinctive ranking sketches, the most important task is to get a uniform representation for action videos. The feature vectors of top m sketches for each video are donated as $\{X'_1, X'_2, \ldots, X'_m\}$. Based on these vectors, our goal is to generate a feature vector X'' with the same d dimensions.

$$X'' = [x''_1, x''_2, \ldots, x''_d]. \tag{7}$$

We apply four kinds of feature pooling methods to achieve the task, respectively are average pooling, max pooling, min pooling and every pooling. For multi-class action classification, we implement these methods and want to find the most suitable one by the evaluation on public human action datasets.

- **Average pooling**. The average operation is performed on the front u feature vectors of top m sketches which is defined as follows,

$$X'' = \sum_{i=1}^{u} X'_i / u. \tag{8}$$

  In fact, it is taking the mean value of each dimension in the u vectors as the new element x''_t of X'',

$$x''_t = \sum_{i=1}^{u} x'_{it} / u, \tag{9}$$

  in which $t = 1, 2, \ldots, d$.
- **Max pooling**. It select the maximum value of the front u feature vectors which is defined as follows,

$$X'' = \max X'_i, \tag{10}$$

  where $i = 1, 2, \ldots, u$. Max pooling means that the new element x''_t equals to the maximum value of each dimension,

$$x''_t = \max x'_{it}. \tag{11}$$

- **Min pooling**. On the contrary to max pooling, it chooses the minimum value of each dimension,

$$x''_t = \min x'_{it}. \tag{12}$$

- **Every pooling**. The aim of every pooling is to produce the chance of representing action video by a single sketch. It simply takes the uth feature vector as a new representation which is defined as follows,

$$X'' = X'_u. \tag{13}$$

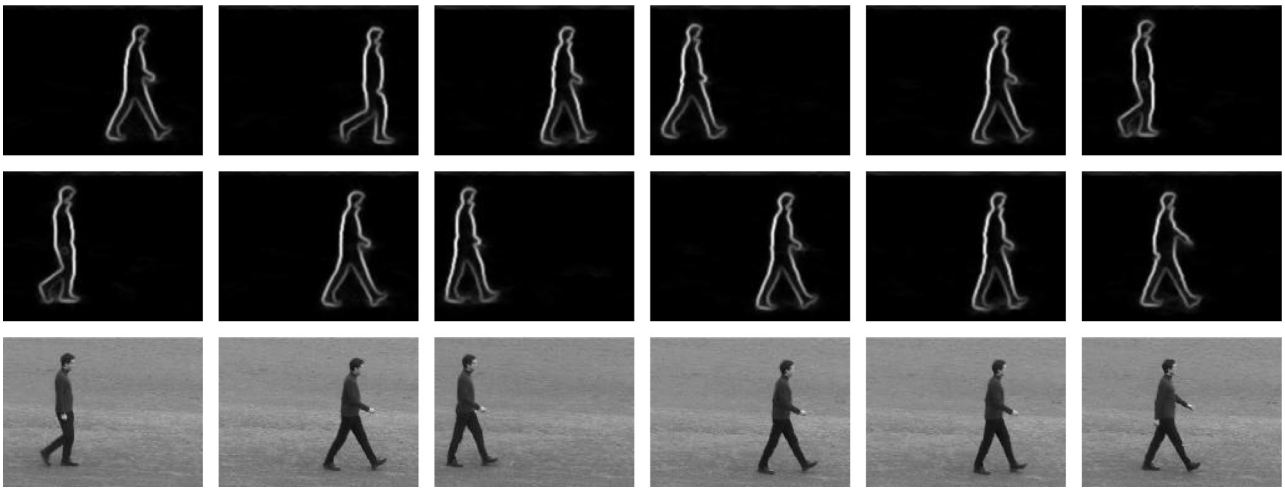


Fig. 2. Illustration of distinctive action sketch mining. Top row: top 6 ranking distinctive action sketches. Second row: results after re-ranking. Third row: original frames corresponding to the re-ranking results.

Although the distinctive action sketch can express spatial information very well, it has a big drawback of lacking temporal cues. In order to solve the problem, we propose to combine the pooling feature and improved dense trajectories (IDT) based features. For representation-level fusion, we concatenate the feature vector of action sketch and the normalized Fisher vectors of IDT descriptors into a single one. The obtained feature vector will be further fed into a linear SVM classifier for action recognition.

6. Experiments

In this section, we describe the detailed experimental settings and show the results on two public human action datasets. We first introduce the datasets used for evaluation and their corresponding experimental setup. Then we present implementation details of our experiments. After that, we evaluate the performance of our method for action recognition and explore different factors that may impact on the final recognition accuracy.

6.1. Datasets

We conduct experiments on two public datasets, respectively are KTH [45] and UCF101 action recognition dataset [46]. The KTH dataset is relatively simple while the UCF101 dataset is more complicated as it is a realistic action dataset collected from YouTube. Some examples of video frames from the two action datasets are illustrated in Figs. 3 and 4.

The KTH dataset consists of 600 video files in total and each class has 100 videos which have a uniform resolutions of 160×120 pixels.[2] The videos are collected from 4 different scenarios and evenly divided into six types of actions: walking, jogging, running, boxing, hand waving and hand clapping. We train models on the training + validation set and report average accuracy for evaluation on the test set.

The UCF101 dataset[3] has 101 action classes and can be divided into five types: Human-Object Interaction, Body-Motion Only, Human-Human Interaction, Playing Musical Instruments, and Sports. We perform evaluation according to the three splits of training and test as described in [46] and present exhaustive results on the dataset.

Although Faster R-CNN is the state-of-the-art object detection method, there still exists lots of action frames that it cannot detect or only detect very few persons. As person detection is a very important part of our method, small number of sketches is not enough to find the most distinctive action sketches. Considering the practical needs and computational cost, we set the max number of top distinctive action sketches $m = 20$ for each video. So the videos will be removed from the original dataset if the number of person detected by Faster R-CNN is less than the max number m. Table 1 gives the number of train/test samples in the two public action datasets after removing some videos. In the following parts, all experiments are conducted on the refined action datasets if not specifically stated.

Table 1
The number of train/test samples in KTH and UCF101 human action datasets after removing the videos that Faster R-CNN detect very few persons.

	KTH	UCF101		
		Split1	Split2	Split3
Train	342	7708	7766	7805
Test	181	3083	3025	2986
Total	523	10,791	10,791	10,791

6.2. Implementation details

For IDT based features, we choose the combined descriptors (HOG + HOF + MBHx + MBHy) with default parameter settings and utilize the implementation of Wang[4] to extract features from action videos. Regarding the feature encoding, the Fisher vector which has shown empirically to give good results is adopted to represent the videos. For the training of Gaussian mixture model (GMM), we randomly sample a subset of 256,000 features to learn GMMS and set the mixture number $K = 256$. Finally, the power and $L2$ normalization are applied to normalize the obtained Fisher vectors of each descriptor type.

In the experiments, we take the linear support vector machine (SVM) which is very efficient in dealing with large data sets as the action recognition classifier. Specifically, we use the code of LIBSVM implemented by Chang et al. [47] released on their website.[5] In the case of multi-class classification, we adopt the one-vs-all approach and select the class with highest score. Besides, we also fix

[2] http://www.nada.kth.se/cvap/actions
[3] http://crcv.ucf.edu/data/UCF101.php
[4] http://lear.inrialpes.fr/~wang/improved_trajectories
[5] http://www.csie.ntu.edu.tw/~cjlin/libsvm

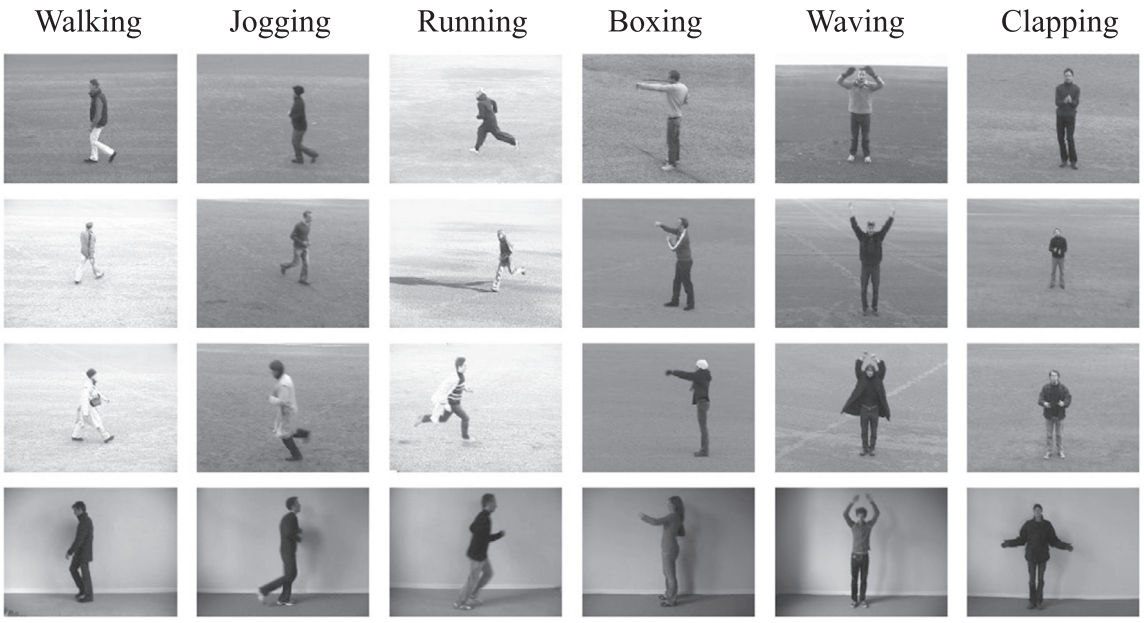


Fig. 3. Sample frames from the KTH human action dataset with six classes (columns) and four scenarios (rows) presented.

Fig. 4. Sample frames of 8 action classes from the UCF101 dataset. From left to right, the first row: ApplyEyeMakeup, Biking, BlowingCandles, Diving. Second row: Haircut, HorseRiding, PlayingViolin, Surfing.

$C = 100$ as described in [27] which has shown good performance. For different sketch pooling methods, we adopt 5-fold cross validation to find the best parameters u and m on the training set.

6.3. Results of distinctive action sketch

We implement our method of distinctive action sketch mining on the six action class of KTH dataset. Fig. 5 shows examples of top 10 distinctive action sketches for each action class. The experimental results demonstrate that different action categories generally have diverse distinctive action sketches (action patterns) and that our method performs well in capturing these sketches. Through these vivid action sketches, the actions can be distinguished conveniently and efficiently. Another point emerged from Fig. 5 is that sketches of quick actions (walking, jogging, running) have more obvious variations than the sluggish action (boxing, hand waving and hand clapping). Furthermore, we can find that there exist many similar patterns in different categories of action sketches. Actually, it is coincident with the intrinsic property in actions, for that sequences between various actions usually share some analogous parts.

In the process of distinctive action sketch mining, a very important factor is the cluster computation by k-means. To analyze the influence of cluster number on final results, we carry out several experiments using different cluster numbers on the KTH dataset. Fig. 6 shows some results of distinctive action sketches under different cluster numbers.

It can be seen that a small number of cluster class yields weak distinctive action sketches. The reason is that a relatively small cluster number will make the results tend to on behalf of those sketches occurred frequently. Along with the increasing of cluster number, we will get more similar distinctive sketches. It means that there is no need to apply a too large number of clusters in pursuit of the results' diversity. It not only cannot improve performance but also will increase the computation cost. In the experiment, we set the cluster number $k = 10$.

6.4. Comparison of different pooling methods

We test the performance of different pooling methods by taking the feature vectors after pooling as the input of action classifier. Because the vectors do not combine with IDT features, so we can evaluate the pure performance when using them alone. Fig. 7 gives a comparison of the four kinds of pooling methods on KTH and UCF101 datasets. The parameter u in pooling process is varying from 1 to 20 while top $m = 20$ distinctive action sketches are

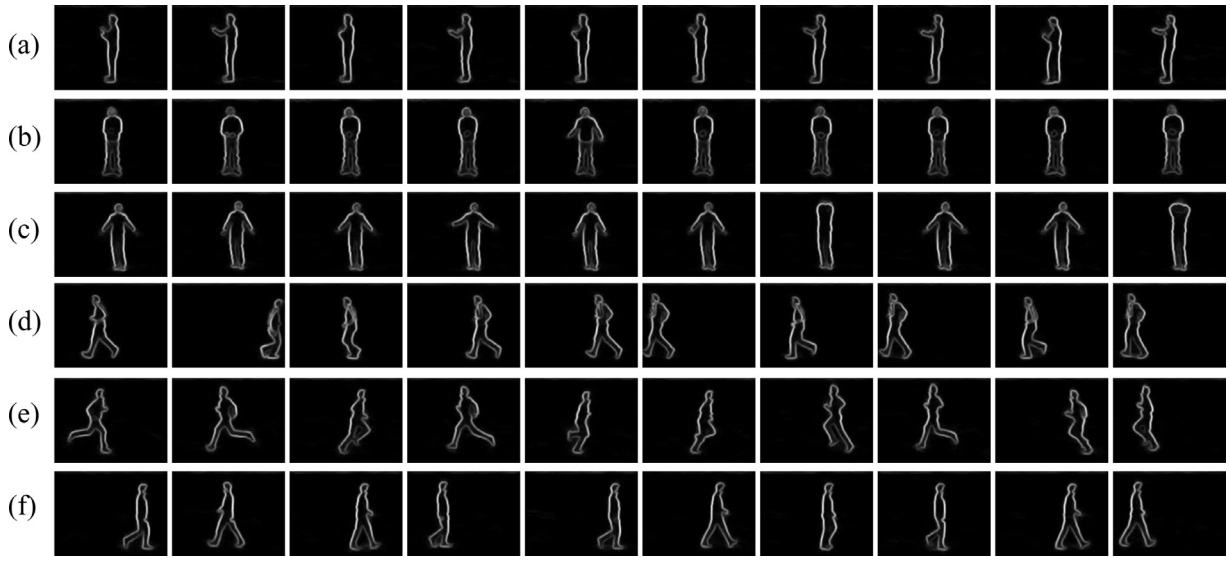


Fig. 5. Examples of top 10 distinctive action sketches for each action class. From top to bottom, they are boxing, hand clapping, hand waving, jogging, running and walking, respectively.

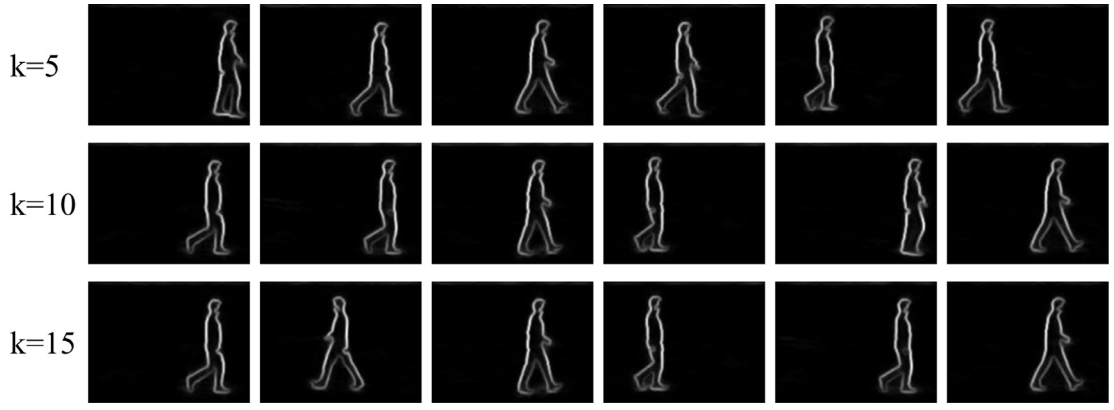
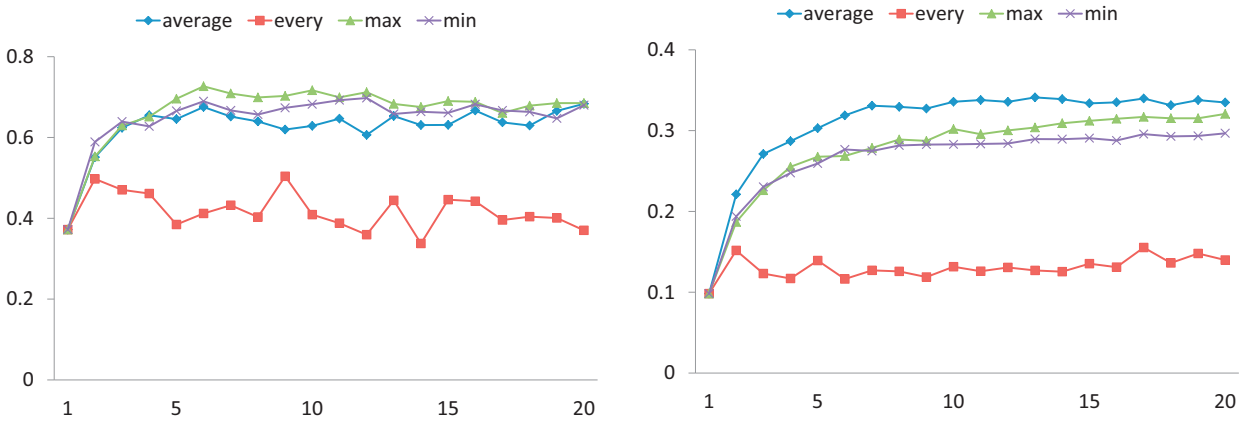


Fig. 6. Results of distinctive action sketches under different cluster numbers. Take the case of walking, from top to bottom is top 6 distinctive action sketches under three kinds of cluster numbers ($k = 5$, $k = 10$, $k = 15$).



(a) KTH (b) UCF101

Fig. 7. Comparison of different pooling methods with varying parameter u on the KTH and UCF101 datasets when $m = 20$.

Table 2
The classification accuracies of different pooling methods and combination with IDT features on the KTH and UCF101 datasets.

	Average		Every		Max		Min	
	Sketch	Comb.	Sketch	Comb.	Sketch	Comb.	Sketch	Comb.
KTH	68.32%	92.66%	53.88%	**94.58%**	72.67%	92.66%	70.44%	92.66%
UCF101	33.98%	83.53%	15.72%	83.59%	32.27%	**83.85%**	31.06%	83.09%

Table 3
Comparison between our method and IDT on the KTH and UCF101 datasets.

		IDT	Ours	Improvement
KTH		91.55%	94.58%	+3.03%
UCF101	split1	79.95%	**81.14%**	+1.19%
	split2	82.99%	**85.14%**	+2.15%
	split3	84.36%	**85.26%**	+0.90%
	Average	82.43%	**83.85%**	+1.42%

Table 4
The best parameters m and u selected for sketch pooling.

	KTH	UCF101		
		Split1	Split2	Split3
m	11	10	18	20
u	6	4	3	20

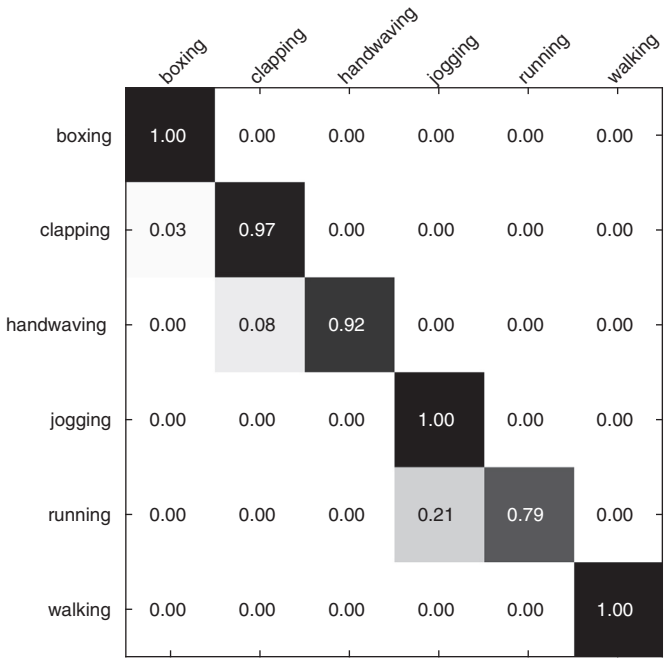


Fig. 8. The confusion matrix of KTH dataset.

Table 5
Comparison of the performance with state-of-the-art methods on UCF101 dataset.

	Accuracy
Spatiotemporal CNN [50]	65.4%
Bimodal encoding [51]	84.2%
C3D(3 net) [52]	85.2%
Two-stream CNN [53]	88.0%
Factorized CNN [54]	88.1%
Two-stream+LSTM [55]	88.6%
TDD+IDT [56]	91.5%
Two-stream fusion+IDT [57]	93.5%
EMV CNN [48]	86.4%
TSN [49]	94.8%
Ours+EMV CNN	89.6%
Ours+TSN	**95.1%**

discovered. We can see that every pooling is the worst method for action recognition. That is to say, it is very difficult to classify the videos represented by one action sketch only. Other three pooling methods achieve good performance on the KTH and UCF101 datasets. For a simple dataset like KTH, the variations of action and backgrounds are very limited. It is possible to classify the action videos through values with the maximum responses. But for the UCF101 dataset, the situation is more complex. Average pooling takes the mean value of top distinctive action sketches as the video representation. It can minimize the negative effect of action variations. As the results shown, the max pooling and average pooling get the highest accuracy on the two datasets respectively. It also demonstrates that the top ranking action sketches are distinctive for action recognition.

Table 2 presents the performance of using different pooling methods alone and gives the accuracies of combination with the Fisher vector of IDT features on the KTH and UCF101 datasets. We can see that the accuracies of action recognition are significantly improved after the representation-level fusion. It is interesting to note that the every pooling get a surprising higher performance than the other pooling methods on the KTH dataset. For the UCF101 dataset, the combination of max pooling based action sketch and IDT features is the best choice for action recognition.

6.5. Results of action recognition

Table 3 shows the action classification accuracies of our method and IDT. As can be seen, the combination of sketch pooling and IDT leads to obvious performance gain. The average performance improvements are 3.03% and 1.42% for KTH and UCF101 datasets respectively. For the KTH dataset, the confusion matrix is shown in Fig. 8. We can see that boxing, jogging and walking are perfectly recognized. For the three splits of UCF101 datasets, we also present the corresponding performance. As can be seen, the highest improvement 2.15% is achieved on the split2. Besides, Table 4 gives all the best parameters m and u selected for sketch pooling on the two datasets. The results of two human action datasets clearly demonstrate the effectiveness of our method.

We also show the comparison against several state-of-the-art methods of action recognition on UCF101 datasets. As a final experiment, we explore the performance of the proposed approach by a late fusion with enhanced motion vector (EMV) CNN [48] and Temporal Segment Networks (TSN) [49]. To get the final output of action video, we simply plus the SVM scores of our method with the predictions for each action class of EMV CNN and TSN. Furthermore, the experiments above are conducted on the refined action datasets as we have mentioned in Section 6.1. For these videos that do not exist in the refined dataset, we directly take the predictions of EMV CNN and TSN as the final outputs. The results are shown in Table 5. Combined with TSN, our method obtains the state-of-the-

Table 6
Runtime (seconds) of different phases on UCF101 dataset.

Sketch mining	Sketch pooling	Training	Test
14167	342	150	1.5

art performance on UCF101 dataset (95.1%). Besides, we achieve 3.2% performance improvement and get 89.6% compared to EMV CNN. It can be seen that our method can provide a significant complementary for the approach based on convolution network.

6.6. Running cost

The distinctive action sketch mining and pooling are the most important parts of our method. It takes roughly 4 h for all videos in the refined UCF101 dataset, excluding the time of feature extraction. Benefits from the linear SVM, the training time on one split is only about 2.5 min while the test time can be negligible. The experiments are performed using Matlab 2014b on a server configured with 24 Intel Xeon E5645 CPU and 64 G of RAM. The detailed running time of different phases are listed in Table 6.

7. Conclusion

Along with the booming development in computer vision, there is an increasing realization that sketch can be an essential element for many realistic applications. Unlike many previous works focusing the representation of action sketch, we mainly explore the available transformation from action to sketch. Before implementation of the specific method, we analyze the characteristics that action sketch must meet and propose a reasonable framework of action sketching. Given the sketches generated under this framework, a distinctive ranking method is presented to mine the most representative sketches in action videos. After that, we perform sketch pooling to obtain a new representation for action recognition. Experimental results demonstrate the effectiveness and excellent performance of our approach.

Acknowledgements

The work was supported in part by the National Science Foundation of China (61472103, 61772158, 61702136, and 61701273) and Australian Research Council (ARC) grant (DP150104645). We especially would like to thank the China Scholarship Council (CSC) for funding the first author to conduct the partially of this project at Australian National University.

References

[1] M. Eitz, K. Hildebrand, T. Boubekeur, M. Alexa, Sketch-based image retrieval: benchmark and bag-of-features descriptors, IEEE Trans. Visual. Comput. Graph. 17 (11) (2011) 1624–1636.
[2] Y. Cao, C. Wang, L. Zhang, L. Zhang, Edgel index for large-scale sketch-based image search, in: IEEE Conference on Computer Vision and Pattern Recognition, 2011, pp. 761–768.
[3] T. Chen, M.-M. Cheng, P. Tan, A. Shamir, S.-M. Hu, Sketch2photo: internet image montage, in: ACM Transactions on Graphics, 28, 2009, p. 124.
[4] K. Xu, K. Chen, H. Fu, W.-L. Sun, S.-M. Hu, Sketch2scene: sketch-based co-retrieval and co-placement of 3d models, ACM Trans. Graph. 32 (4) (2013) 123.
[5] J.P. Collomosse, G. McNeill, Y. Qian, Storyboard sketches for content based video retrieval, in: IEEE International Conference on Computer Vision, 2009, pp. 245–252.
[6] R. Hu, S. James, T. Wang, J. Collomosse, Markov random fields for sketch based video retrieval, in: ACM International Conference on Multimedia Retrieval, 2013, pp. 279–286.
[7] Z. Sun, C. Wang, L. Zhang, L. Zhang, Free hand-drawn sketch segmentation, in: Europeon Conference on Computer Vision, Springer, 2012, pp. 626–639.
[8] Y. Zheng, H. Yao, S. Zhao, Y. Wang, Discovering discriminative patches for free–hand sketch analysis, Multimed. Syst. (2016) 1–11.
[9] M. Eitz, J. Hays, M. Alexa, How do humans sketch objects? ACM Trans. Graph. 31 (4) (2012) 44.
[10] Z. Sun, C. Wang, L. Zhang, L. Zhang, Query-adaptive shape topic mining for hand-drawn sketch recognition, in: ACM International Conference on Multimedia, 2012, pp. 519–528.
[11] R. Poppe, A survey on vision-based human action recognition, Image Vision Comput. 28 (6) (2010) 976–990.
[12] S. Zhao, L. Chen, H. Yao, Y. Zhang, X. Sun, Strategy for dynamic 3d depth data matching towards robust action retrieval, Neurocomputing 151 (2015) 533–543.
[13] A. Yilmaz, M. Shah, Actions sketch: a novel action representation, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 1, 2005, pp. 984–989.
[14] P. Dollár, C.L. Zitnick, Structured forests for fast edge detection, in: IEEE International Conference on Computer Vision, 2013, pp. 1841–1848.
[15] S. Ren, K. He, R. Girshick, J. Sun, Faster r-cnn: Towards real-time object detection with region proposal networks, in: Advances in Neural Information Processing Systems, 2015, pp. 91–99.
[16] Y. Zheng, H. Yao, X. Sun, X. Jiang, F. Porikli, Breaking video into pieces for action recognition, Multimed. Tools Appl. (2017) 1–18.
[17] D. Weinland, R. Ronfard, E. Boyer, A survey of vision-based methods for action representation, segmentation and recognition, Comput. Vision Image Understand. 115 (2) (2011) 224–241.
[18] X. Peng, L. Wang, X. Wang, Y. Qiao, Bag of visual words and fusion methods for action recognition: comprehensive study and good practice, Comput. Vision Image Understand. (2016).
[19] Y. Ke, R. Sukthankar, M. Hebert, Spatio-temporal shape and flow correlation for action recognition, in: IEEE Conference on Computer Vision and Pattern Recognition, 2007, pp. 1–8.
[20] A. Klaser, M. Marszałek, C. Schmid, A spatio-temporal descriptor based on 3d–gradients, in: British Machine Vision Conference, 2008, pp. 275:1–10.
[21] S. Zhang, H. Yao, X. Sun, K. Wang, J. Zhang, X. Lu, Y. Zhang, Action recognition based on overcomplete independent components analysis, Inform. Sci. 281 (2014) 635–647.
[22] H. Wang, M.M. Ullah, A. Klaser, I. Laptev, C. Schmid, Evaluation of local spatio-temporal features for action recognition, in: British Machine Vision Conference, 2009, pp. 124:1–11.
[23] C. Xu, D. Tao, C. Xu, A survey on multi-view learning, 2013 1304.5634.
[24] W. Liu, H. Liu, D. Tao, Y. Wang, K. Lu, Multiview hessian regularized logistic regression for action recognition, Signal Process. 110 (2015) 101–107.
[25] S. Zhao, H. Yao, Y. Gao, R. Ji, G. Ding, Continuous probability distribution prediction of image emotions via multitask shared sparse regression, IEEE Trans. Multimed. 19 (3) (2017) 632–645.
[26] I. Laptev, On space-time interest points, Int. J. Comput. Vision 64 (2–3) (2005) 107–123.
[27] H. Wang, C. Schmid, Action recognition with improved trajectories, in: IEEE International Conference on Computer Vision, 2013, pp. 3551–3558.
[28] I. Laptev, M. Marszałek, C. Schmid, B. Rozenfeld, Learning realistic human actions from movies, in: IEEE Conference on Computer Vision and Pattern Recognition, 2008, pp. 1–8.
[29] W. Liu, D. Tao, Multiview hessian regularization for image annotation, IEEE Trans. Image Process. 22 (7) (2013) 2676–2687.
[30] L. Shao, L. Liu, M. Yu, Kernelized multiview projection for robust action recognition, Int. J. Comput. Vision 118 (2) (2016) 115.
[31] Y. Zheng, H. Yao, X. Sun, S. Zhao, Distinctive action sketch, in: IEEE International Conference on Image Processing, 2015, pp. 576–580.
[32] C. Hong, X. Chen, X. Wang, C. Tang, Hypergraph regularized autoencoder for image-based 3d human pose recovery, Signal Process. 124 (2016) 132–140.
[33] C. Hong, J. Yu, D. Tao, M. Wang, Image-based three-dimensional human pose recovery by multiview locality-sensitive sparse retrieval, IEEE Trans. Industr. Electron. 62 (6) (2015) 3742–3751.
[34] C. Hong, J. Yu, J. Wan, D. Tao, M. Wang, Multimodal deep autoencoder for human pose recovery, IEEE Trans. Image Process. 24 (12) (2015) 5659–5670.
[35] H. Rahmani, A. Mahmood, D. Huynh, A. Mian, Histogram of oriented principal components for cross-view action recognition, IEEE Trans. Pattern Anal. Mach. Intell. 38 (12) (2016) 2430–2443.
[36] R. Vemulapalli, F. Arrate, R. Chellappa, Human action recognition by representing 3d skeletons as points in a lie group, in: IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 588–595.
[37] Z. Han, Z. Xu, S.-C. Zhu, Video primal sketch: a generic middle-level representation of video, in: IEEE International Conference on Computer Vision, 2011, pp. 1283–1290.
[38] B. Yao, S.-C. Zhu, Learning deformable action templates from cluttered videos, in: IEEE International Conference on Computer Vision, 2009, pp. 1507–1514.
[39] C.-e. Guo, S.-C. Zhu, Y.N. Wu, Primal sketch: integrating structure and texture, Comput. Vision Image Understand. 106 (1) (2007) 5–19.
[40] Q. Fang, J. Sang, C. Xu, Giant: Geo-informative attributes for location recognition and exploration, in: ACM International Conference on Multimedia, 2013, pp. 13–22.
[41] J. Sang, Q. Fang, C. Xu, Exploiting social-mobile information for location visualization, ACM Trans. Intell. Syst. Technol. 8 (3) (2017) 39.
[42] A. Razavian, H. Azizpour, J. Sullivan, S. Carlsson, Cnn features off-the-shelf: an astounding baseline for recognition, in: IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2014, pp. 806–813.
[43] Q. Yu, Y. Yang, Y.-Z. Song, T. Xiang, T.M. Hospedales, Sketch-a-net that beats humans, in: British Machine Vision Conference, 2015, pp. 1–12.

[44] K. Simonyan, A. Zisserman, Very deep convolutional networks for large-scale image recognition, 2014. arXiv preprint arXiv: 1409.1556.
[45] C. Schuldt, I. Laptev, B. Caputo, Recognizing human actions: a local svm approach, in: IEEE International Conference on Pattern Recognition, 3, 2004, pp. 32–36.
[46] K. Soomro, A.R. Zamir, M. Shah, Ucf101: a dataset of 101 human actions classes from videos in the wild, 2012. arXiv preprint arXiv: 1212.0402.
[47] C.-C. Chang, C.-J. Lin, Libsvm: a library for support vector machines, ACM Trans. Intell. Syst. Technol. 2 (3) (2011) 27.
[48] B. Zhang, L. Wang, Z. Wang, Y. Qiao, H. Wang, Real-time action recognition with enhanced motion vector cnns, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2718–2726.
[49] L. Wang, Y. Xiong, Z. Wang, Y. Qiao, D. Lin, X. Tang, L. Van Gool, Temporal segment networks: towards good practices for deep action recognition, in: European Conference on Computer Vision, 2016, pp. 20–36.
[50] A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, L. Fei-Fei, Large-scale video classification with convolutional neural networks, in: IEEE conference on Computer Vision and Pattern Recognition, 2014, pp. 1725–1732.
[51] J. Wu, Y. Zhang, W. Lin, Towards good practices for action video encoding, in: IEEE conference on Computer Vision and Pattern Recognition, 2014, pp. 2577–2584.
[52] D. Tran, L. Bourdev, R. Fergus, L. Torresani, M. Paluri, Learning spatiotemporal features with 3d convolutional networks, in: IEEE International Conference on Computer Vision, 2015, pp. 4489–4497.
[53] K. Simonyan, A. Zisserman, Two-stream convolutional networks for action recognition in videos, in: Advances in Neural Information Processing Systems, 2014, pp. 568–576.
[54] L. Sun, K. Jia, D.-Y. Yeung, B.E. Shi, Human action recognition using factorized spatio-temporal convolutional networks, in: IEEE International Conference on Computer Vision, 2015, pp. 4597–4605.
[55] J. Yue-Hei Ng, M. Hausknecht, S. Vijayanarasimhan, O. Vinyals, R. Monga, G. Toderici, Beyond short snippets: deep networks for video classification, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 4694–4702.
[56] L. Wang, Y. Qiao, X. Tang, Action recognition with trajectory-pooled deep-convolutional descriptors, in: IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 4305–4314.
[57] C. Feichtenhofer, A. Pinz, A. Zisserman, Convolutional two-stream network fusion for video action recognition, in: IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 1933–1941.