Computer Vision Notes

Action Recognition (Early Approaches)

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Acknowledgements

- Rohit G., “Deep Learning for Videos: A 2018 Guide to Action Recognition”, Qure.ai Blog, June, 2018. link
- Sullivan and Carlsson, “Recognizing and Tracking Human Actions”
- Gall J., “Action Recognition”, CVPR 13 Tutorial.
- Figures from Schuldt et al., “Recognizing Human Actions: A Local SVM Approach,” ICPR 2004.
- Figures from Niebles et al., “Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words,” IJCV 2008.
- Figures from Zisserman and Carreira, “Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset,” arXiv:1705.07750v3, 2018.

Action Recognition Applications

- Surveillance footage
- User-interfaces
- Automatic video organization

Challenges

- Occlusions
- Scale
- Camera movement
- Presence of multiple actions
- Clutter (background)
- Variations in how actions are performed

Paper 1

Schuldt et al., “Recognizing Human Actions: A Local SVM Approach,” ICPR 2004.

Spatio Temporal Interest Points

- Construct scale-space representation $L(., \sigma^2, \tau^2)$ using Gaussian convolutional kernel.
- Compute second-moment matrix ∇L within Gaussian neighborhood of each point
- Define feature positions using local maxima of H.

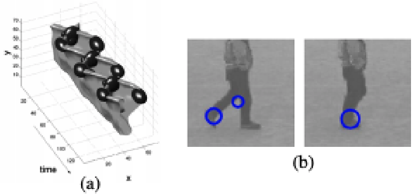


Figure 1. Local space-time features detected for a walking pattern: (a) 3-D plot of a spatio-temporal leg motion (up side down) and corresponding features (in black); (b) Features overlaid on selected frames of a sequence.

Spatio-Temporal Feature Descriptors

- Spatio-temporal neighborhoods of local features contain information about the motion and the spatial appearance of events in image sequences.
- Compute spatio-temporal jets (descriptors) to capture this information $l = (L_x, L_y, L_t, L_{xx}, \cdots, L_{tttt})$.
- Cluster descriptors l using K-means. This gives us a vocabulary of primitive events h_i.
- Compute histogoram $H = (h_1, \cdots, h_n)$, where bin h_i count the number of features with label h_i.

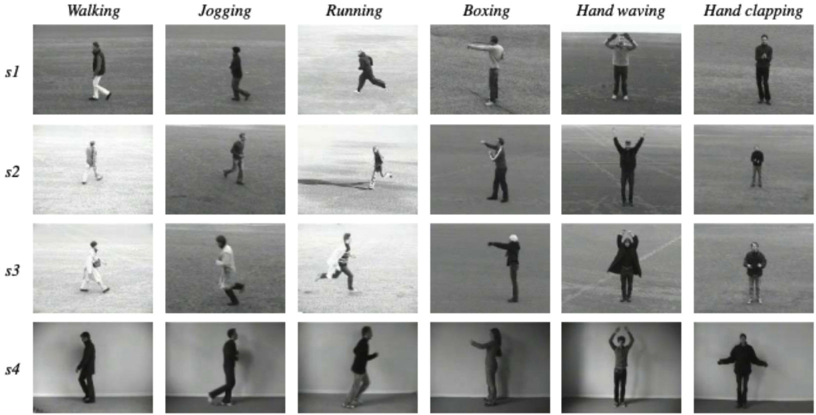


Figure 2. Action database (available on request): examples of sequences corresponding to different types of actions and scenarios.

Evalution

Representations

1. Local features described by spatio-temporal jets of order 4 (LF)
2. 128-bin histograms of local features (HistLF)
3. Marginalized histograms of normalized spatial temporal gradients (HistSTG)

Classifiers

1. Support Vector Machine (SVM)
2. Nearest Neighbor Classifier (NNC)

Observations

- LF with SVM gives the best performance.
- SVM gives better performance than NNC on HistLF and HistSTG, with HistLF performing slightly better than HistSTG.
- Supervised learning approach

Matching Local Features

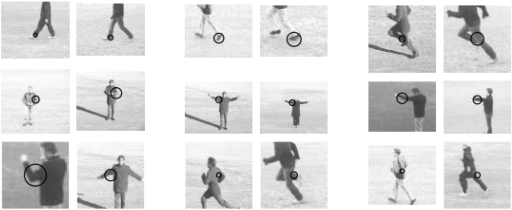


Figure 4. Examples of matched features in different sequences. (top): Correct matches in sequences with leg actions; (middle): Correct matches in sequences with arm actions; (bottom): false matches.

- The pairs correspond to features with jet descriptors l_{jh} and l_{jk} selected by maximizing the feature kernel over j_k in

$$K(L_h, L_k) = \frac{1}{n_h} \sum_{j_h=1}^{n_h} \max_{j_h=1,\cdots,n_k} K_l(l_{jh}, l_{jk})$$

Dataset

- Backgrounds are mostly free of clutter
- Single actor
- 25 people, each
  - 6 actions (walking, jogging, running, boxing, hand waving, clapping)
  - 4 scenarios (outdoors, outdoors + scale, outdoors + different clothes, indoors)

Paper 2

Niebles et al., "Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words," IJCV 2008.

Approach

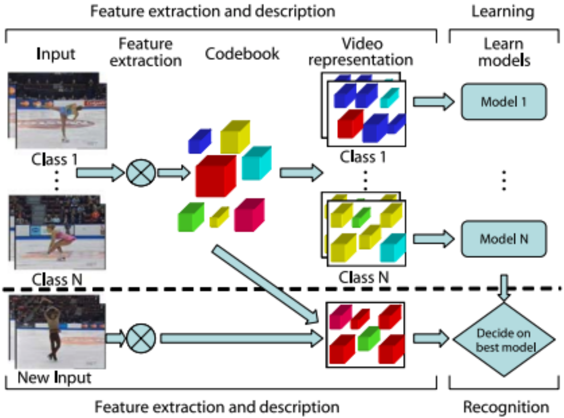
- Learn different classes of actions present in a collection of unlabeled videos.
- Classify actions in previously unseen videos by applying the learned models.
- Similar to Hofmann, T. (1999). "Probabilistic latent semantic indexing." In Proceedings of the 22nd annual international ACM SIGIR conference on research and development in information retrieval (pp. 50–57), August 1999.

Assumptions

- Videos may contain a small amount of camera motion.
- Videos may contains some amount of background clutter.
- **Training:** videos contains a single actor.
- **Testing:** videos may contain more than one actors.

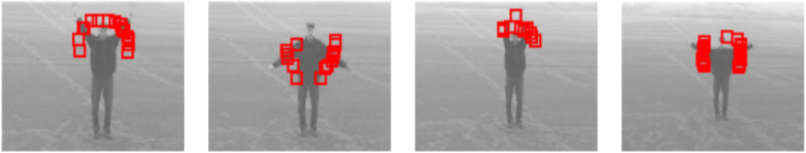
Approach

- Extract local space-time regions using space-time interest point detector.
- Cluster these regions in a codebook.
- Learn probability distributions and discover latent topics using.
- Use the learned model to recognize and localize human action classes.



Space-time interest point detectors

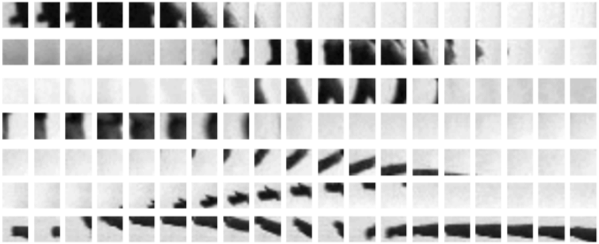
- Separable linear filters (2D Gaussian + 1D Gabor).
- Extract a small video cube around each interest point.



Video Representation as a Bag of Visual Words

Space-time descriptors

- Histogram of brightness gradient at each feature point.
  - Gradients concatenated to form feature vector.
  - Use PCA for reducing dimensionality.
- K-means clustering of video word descriptors to construct the codebook.



Video representation

- Histogram of video words from the codebook.

Model (learning probabilities and latent topics)

Given an input video d_j and video words w_i, we can write the joint probability as follows:

$$p(d_j, w_i) = p(w_i|d_j)p(d_j).$$

Furthmore, given a set of (latent) actions z_k, where $k = 1, \cdots, K$,

$$p(w_i|d_j) = \sum_{k=1}^{K} p(w_i|z_k)p(z_k|d_j).$$

Here K is the number of action categories, $p(z_k|d_j)$ are action category weights and $p(w_i|z_k)$ are action category vectors.

Use probablistic Latent Semantic Analysis (pLSA) or Latent Dirichlet Allocation (LDA) to learn the above model.

Classification

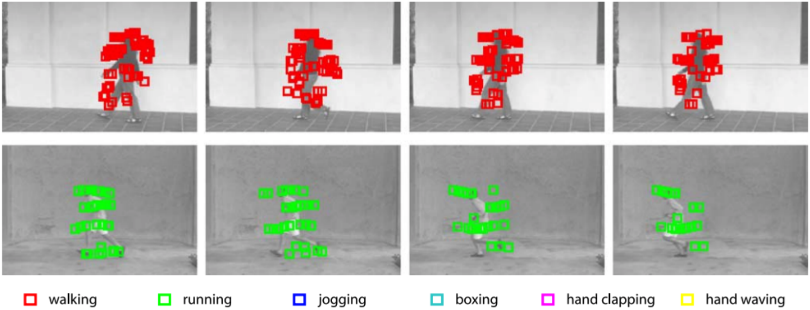
Given a new video and the learnt model, we can classify it as belonging to one of the action categories using

$$\arg\max_k P(z_k|d_{\text{test}}).$$

Recall

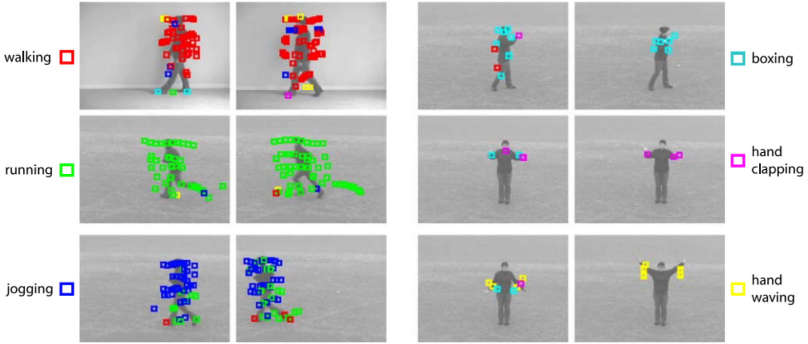
$$p(w|d_{\text{test}}) = \sum_{k=1}^{K} P(z_k|d_{\text{test}})p(w|z_k).$$

CalTech Dataset



Words colored according to their most likely action category.

KTH Datasets



Words colored according to their most likely action category.

Performance on KTH Dataset

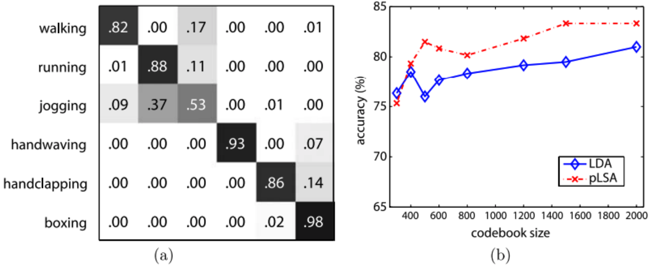
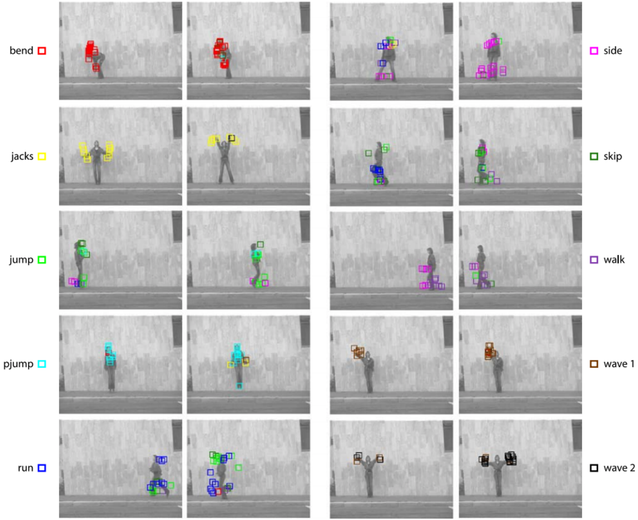


Fig. 8 (**a**) Confusion matrix for the KTH dataset using 1500 codewords (performance average = 83.33%); *rows* are ground truth, and *columns* are model results; (**b**) Classification accuracy vs. codebook size for the KTH dataset. Experiments show that the results for the recognition task are consistently better when the pLSA model is adopted

Weizmann Human Action Dataset



Performance on Weizmann Human Action Dataset

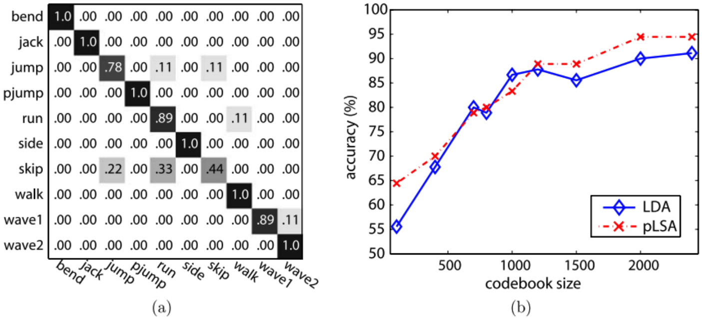
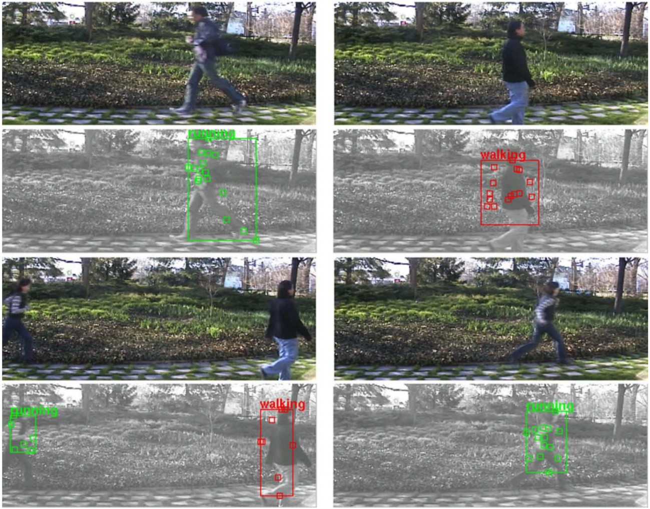


Fig. 13 (**a**) Confusion matrix for the Weizmann human action dataset (Blank et al. 2005); *rows* are ground truth, and *columns* are model results. The action models learnt with pLSA and using 1200 codewords show an average performance of 90%. (**b**) Classification accuracy obtained using pLSA and LDA models vs. codebook size. Our results show that pLSA performs slightly better than LDA in the video categorization task

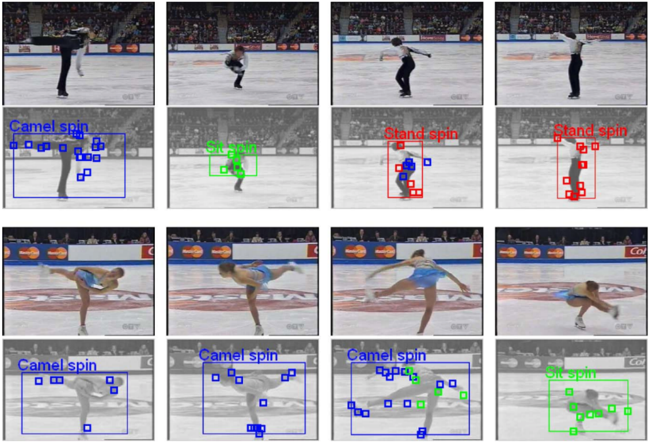
Dealing with multiple actions

1. Select topics with high $p(z_k|d_{\text{test}})$
2. Assign words to topics using $p(w|z_k)$
3. Cluster words from selected topics according to their spatial position

Dealing with multiple actions - Spatial Localization

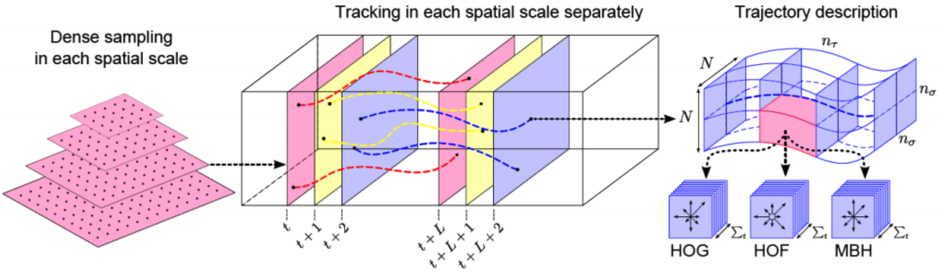


Dealing with multiple actions - Localization in Time



Tracking Local Representations for Action Recognition

- Wang et al., "Action Recognition by Dense Trajectories," CVPR 2011.

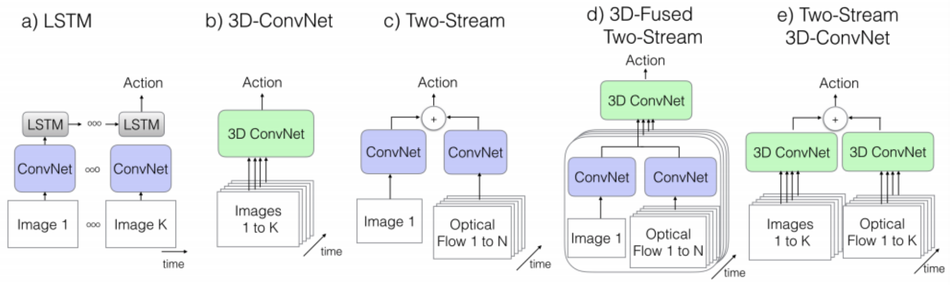


- Histogram of Oriented Gradients (HOG)
- Histogram of Optical Flow (HOF)
- Motion Boundary Histogram (MBH)

Paper 3 - Deep Learning and Action Recgnition

Zisserman and Carreira, "Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset," arXiv:1705.07750v3, 2018.

Architectures (Before 2018)



ConvNET + LSTM (Fig. a)

- Compute deep features from image classification networks
- Benefits from ImageNet pre-training

Approach 1

- Pool deep features (as in bag of visual words) to perform action classification.
- **Drawbacks:** Ignore temporal structure. So, these approaches, for example, cannot distinquish between opening a door and closing a door.

Approach 2

- Feed deep features to LSTM to capture temporal structure.
- **Drawbacks:** LSTM using last layer features doesn't capture low-level information (such as optical flow).

3D ConvNets (Fig. b)

- Computes spatio-temporal deep features.
- Creates hierarchical representations of spatio-temporal data.

Drawbacks

- A lot more parameters as compared to 2D ConvNets.
- Precludes ImageNet pre-training.

Two-Stream Networks (Fig. c, d and e)

- RGB stream + flow stream
- [1] models short temporal snapshots of videos by averaging the predictions from a single RGB frame and a stack of 10 externally computed optical.
- A recent extension [2] fuses the spatial and flow streams after the last network convolutional layer, showing some improvement on HMDB while requiring less test time augmentation (snapshot sampling).

Two-Stream Inflated 3D ConvNets

- Convert successful image (2D) classification models into 3D ConvNets.
- Given a 2D architecture (trainined on, say, ImageNet), inflate all the filters and pooling kernels.
  - An $N \times N$ filter becomes $N \times N \times N$ filter.
- Bootstrap 3D filters from 2D filters using by using "boring videos"
  - An image can be made into a boring video by copying it repeatedly into a video sequence.
- Carefully control receptive field growth in space and time

Two-Stream Inflated 3D ConvNets

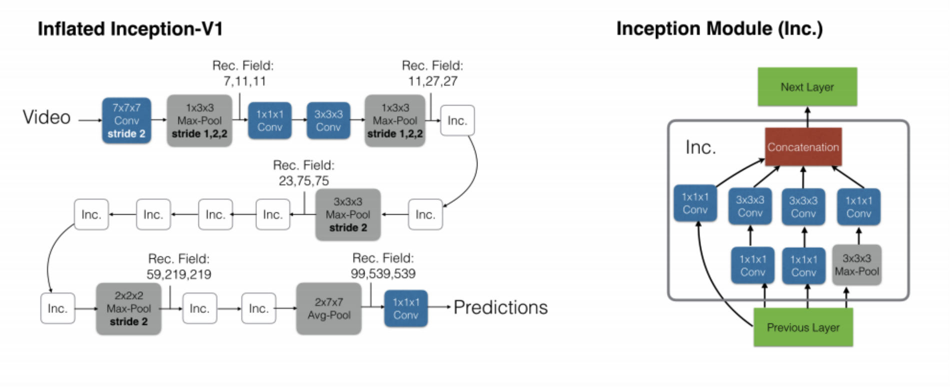


Figure 3. The Inflated Inception-V1 architecture (left) and its detailed inception submodule (right). The strides of convolution and pooling operators are 1 where not specified, and batch normalization layers, ReLu's and the softmax at the end are not shown. The theoretical sizes of receptive field sizes for a few layers in the network are provided in the format "time,x,y" – the units are frames and pixels. The predictions are obtained convolutionally in time and averaged.

Evaluations

Architecture	UCF-101			HMDB-51		
	Original	Fixed	Full-FT	Original	Fixed	Full-FT
(a) LSTM	81.0 / 54.2	88.1 / 82.6	91.0 / 86.8	36.0 / 18.3	50.8 / 47.1	53.4 / 49.7
(b) 3D-ConvNet	– / 51.6	– / 76.0	– / 79.9	– / 24.3	– / 47.0	– / 49.4
(c) Two-Stream	91.2 / 83.6	93.9 / 93.3	94.2 / 93.8	58.3 / 47.1	66.6 / 65.9	66.6 / 64.3
(d) 3D-Fused	89.3 / 69.5	94.3 / 89.8	94.2 / 91.5	56.8 / 37.3	69.9 / 64.6	71.0 / 66.5
(e) Two-Stream I3D	93.4 / 88.8	97.7 / 97.4	98.0 / 97.6	66.4 / 62.2	79.7 / 78.6	81.2 / 81.3

Table 4. Performance on the UCF-101 and HMDB-51 test sets (split 1 of both) for architectures starting with / without ImageNet pretrained weights. Original: train on UCF-101 or HMDB-51; Fixed: features from Kinetics, with the last layer trained on UCF-101 or HMDB-51; Full-FT: Kinetics pre-training with end-to-end fine-tuning on UCF-101 or HMDB-51.

Evaluations

Model	UCF-101	HMDB-51
Two-Stream [27]	88.0	59.4
IDT [33]	86.4	61.7
Dynamic Image Networks + IDT [2]	89.1	65.2
TDD + IDT [34]	91.5	65.9
Two-Stream Fusion + IDT [8]	93.5	69.2
Temporal Segment Networks [35]	94.2	69.4
ST-ResNet + IDT [7]	94.6	70.3
Deep Networks [15], Sports 1M pre-training	65.2	-
C3D one network [31], Sports 1M pre-training	82.3	-
C3D ensemble [31], Sports 1M pre-training	85.2	-
C3D ensemble + IDT [31], Sports 1M pre-training	90.1	-
RGB-I3D, Imagenet+Kinetics pre-training	95.6	74.8
Flow-I3D, Imagenet+Kinetics pre-training	96.7	77.1
Two-Stream I3D, Imagenet+Kinetics pre-training	**98.0**	80.7
RGB-I3D, Kinetics pre-training	95.1	74.3
Flow-I3D, Kinetics pre-training	96.5	77.3
Two-Stream I3D, Kinetics pre-training	97.8	**80.9**

Table 5. Comparison with state-of-the-art on the UCF-101 and HMDB-51 datasets, averaged over three splits. First set of rows contains results of models trained without labeled external data.

Datasets

- UCF101
- HMDB-51
- Kinectics

From Actions to Activity to Behavior

The Heider-Simmel Illusion

References

1. Simonyan K, Zisserman A (2014) Two-stream convolutional networks for action recognition in videos. In: Advances in neural information processing systems. pp 569–576

2. Feichtenhofer C, Pinz A, Zisserman A (2016) Convolutional two-stream network fusion for video action recognition. In: IEEE international conference on computer vision and pattern recognition CVPR