Action Recognition by Matching Clustered Trajectories of Motion Vectors

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Abstract: A framework for action representation and recognition based on the description of an action by time series of optical flow motion features is presented. In the learning step, the motion curves representing each action are clustered using Gaussian mixture modeling (GMM). In the recognition step, the optical flow curves of a probe sequence are also clustered using a GMM and the probe curves are matched to the learned curves using a non-metric similarity function based on the longest common subsequence which is robust to noise and provides an intuitive notion of similarity between trajectories. Finally, the probe sequence is categorized to the learned action with the maximum similarity using a nearest neighbor classification scheme. Experimental results on common action databases demonstrate the effectiveness of the proposed method.

1 INTRODUCTION

Action recognition is a preponderant and difficult task in computer vision. Many applications, including video surveillance systems, human-computer interaction and robotics to human behavior characterization, require a multiple activity recognition system.

The problem of categorizing a human action remains a challenging task that has attracted much research effort in the recent years. The surveys in (Aggarwal and Ryoo, 2011) and (Poppe, 2010) provide a good overview of the numerous papers on action/activity recognition and analyze the semantics of human activity categorization. Several feature extraction methods for describing and recognizing human actions have been proposed (Efros et al., 2003; Schuldt et al., 2004; Jhuang et al., 2007; Niebles et al., 2008; Fathi and Mori, 2008). A major family of methods relies on optical flow which has proven to be an important cue. In (Efros et al., 2003), human actions are recognized from low-resolution sports video sequences using the nearest neighbor classifier, where humans are represented by windows of height of 30 pixels. The approach in (Fathi and Mori, 2008) is based on mid-level motion features, which are also constructed directly from the optical flow features. Moreover, Wang and Mori employed motion features as inputs to hidden conditional random fields and support vector machine (SVM) classifiers (Wang and Mori, 2011). Real time classification and prediction of future actions is proposed in (Morris and Trivedi, 2011), where an activity vocabulary is learnt through a three step procedure. Other optical flow-based methods which gained popularity are presented in (Lin et al., 2009; Chaudhry et al., 2009).

The classification of a video sequence using local features in a spatio-temporal environment has been given much focus. Schuldt et al. represent local events in a video using space-time features, while an SVM classifier is used to recognize an action (Schuldt et al., 2004). In (Gorelick et al., 2007), actions are considered as 3D space time silhouettes of moving humans. They take advantage of the Poisson equation solution to efficiently describe an action by utilizing spectral clustering between sequences of features and applying nearest neighbor classification to characterize an action. Niebles et al. address the problem of action recognition by creating a codebook of space-time interest points (Niebles et al., 2008). A hierarchical approach was followed in (Jhuang et al., 2007), where an input video is analyzed into several feature descriptors depending on their complexity. The final classification is performed by a multi-class SVM classifier. In (Dollár et al., 2005), spatio-temporal features are proposed based on cuboid descriptors. An action descriptor of histograms of interest points, re-

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lying on (Schuldt et al., 2004) was presented in (Yan and Luo, 2012). Random forests for action representation have also been attracting widespread interest for action recognition (Yao et al., 2010). Furthermore, the key issue of how many frames are required for action recognition is addressed in (Schindler and Gool, 2008).

In this paper, we address the problem of human action recognition by representing an action with a set of clustered motion trajectories. Motion curves are generated by optical flow features which are then clustered using a different Gaussian mixture (Bishop, 2006) for each distinct action. The optical flow curves of a probe sequence are also clustered using a Gaussian mixture model (GMM) and they are matched to the learned curves using a similarity function (Vlachos et al., 2002) relying on the longest common subsequence (LCSS) between trajectories. The LCSS is robust to noise and provides an intuitive notion of similarity between trajectories. Since different actors perform the same action in different manners and at different speeds, an advantage of the LCSS similarity is that it can handle with motion trajectories of varied lengths.

The main contribution of the paper is twofold. At first, human motion is represented by a small set of trajectories which are the mean curves of the mixture components along with their covariance matrices. The complexity of the model is considered low, as it is determined by the Bayesian Information Criterion (BIC), but any other model selection technique may be applied. Secondly, the use of the longest common subsequence index allows input curves of different length to be compared reliably.

The rest of the paper is organized as follows: we represent the extraction of motion trajectories, the clustering and the curve matching in Section 2. In Section 3, we report results on the Weizmann (Blank et al., 2005) and the KTH (Schuldt et al., 2004) action classification datasets. Finally, conclusions are drawn in Section 4.

2 ACTION REPRESENTATION AND RECOGNITION

Our goal is to analyze and interpret different classes of actions to build a model for human activity categorization. Given a collection of figure-centric sequences, we represent motion templates using optical flow (Lucas and Kanade, 1981) at each frame. Assuming that a bounding box can be automatically obtained from the image data, we define a square region of interest (ROI) around the human. A brief overview of our approach is depicted in Figure 1. In the training mode, we assume that the video sequences contain only one actor performing only one action per frame. However, in the recognition mode, we allow more than one action per video frame. The optical flow vectors as well as the motion descriptors (Efros et al., 2003) for each sequence are computed. These motion descriptors are collected together to construct motion curves, which are clustered using a mixture model to describe a unique action. Then, the motion curves are clustered and each action is characterized by a set of clustered motion curves. Action recognition is performed by matching the clusters of motion curves of the probe sequence and the clustered curves in each training sequence.

2.1 Motion Representation

Following the work in (Efros et al., 2003), we compute the motion descriptor for the ROI as a four-dimensional vector $\mathbf{F}_i = \left(F_{x_i}^+, F_{x_i}^-, F_{y_i}^+, F_{y_i}^-\right) \in \mathbb{R}^4$, where $i = 1, \ldots, N$, with N being the number of pixels in the ROI. Also, the matrix $\mathbf{F}$ refers to the blurred, motion compensated optical flow. We compute the optical flow $\mathbf{F}$, which has two components, the horizontal F_x, and the vertical F_y, at each pixel. It is worth noting that the horizontal and vertical components of the optical flow F_x and F_y are half-wave rectified into four non-negative channels $F_x^+, F_x^-, F_y^+, F_y^-$, so that $F_x = F_x^+ - F_x^-$ and $F_y = F_y^+ - F_y^-$. In the general case, optical flow is suffering from noisy measurements and analyzing data under these circumstances will lead to unstable results. To handle any motion artifacts due to camera movements, each half-wave motion compensated flow is blurred with a Gaussian kernel. In this way, the substantive motion information is preserved, while minor variations are discarded. Thus, any incorrectly computed flows are removed.

2.2 Extraction of Motion Curves

Consider T to be the number of image frames and $\mathrm{C} = \{c_i(t)\}, t \in [0, T]$, is a set of motion curves for the set of pixels $i = 1, \ldots, N$ of the ROI. Each motion curve is described as a set of points corresponding to the optical flow vector extracted in the ROI. Specifically, we describe the motion at each pixel by the optical flow vector $\mathbf{F}_i = \left(F_{x_i}^+, F_{x_i}^-, F_{y_i}^+, F_{y_i}^-\right)$. A set of motion curves for a specific action is depicted in Figure 1. Given the set of motion descriptors for all frames, we construct the motion curves by following their optical flow components in consecutive frames. If there is no pixel displacement we consider a zero optical flow vector displacement for this pixel.

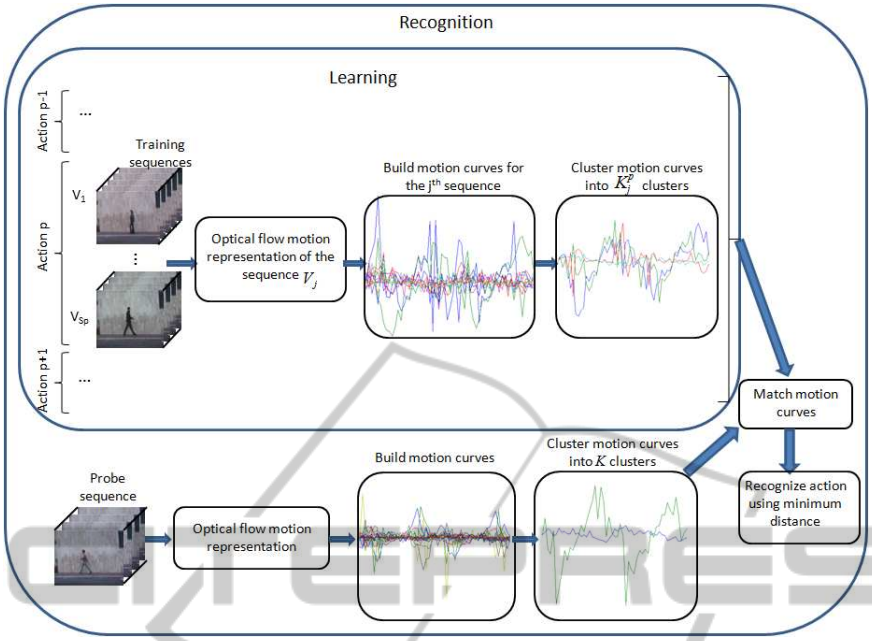


Figure 1: Overview of our approach.

The set of motion curves describes completely the motion in the ROI. Once the motion curves are created, pixels and therefore curves that belong to the background are eliminated. This is accomplished by discarding curves whose amplitude of the optical flow vector is below a predefined threshold. In order to establish a correspondence between the motion curves and the actual motion, we perform clustering of the motion curves using a Gaussian mixture model. We estimate the characteristic motion which is represented by the mean trajectory of each cluster.

2.3 Motion Curves Clustering

A motion curve is considered to be a 2D time signal $c_{ji}(t) = \left(F_{x_{ji}}(t), F_{y_{ji}}(t)\right), t \in [0,T]$ where the index $i = 1,\ldots,N$ represents the i^{th} pixel, for the j^{th} video sequence in the training set. To efficiently learn human action categories, each action is represented by a GMM by clustering the motion curves in every sequence of the training set. The p^{th} action ($p = 1,...,A$) in the j^{th} video sequence ($j = 1,\ldots,S_p$) is modeled by a set of K_j^p mean curves (learned by the GMM) denoted by $x_{jk}^p(t)$, $k = 1,...,K_j^p$.

The GMM is trained using the Expectation-Maximization (EM) algorithm (Bishop, 2006), which provides a solution to the problem of estimating the model's parameters. However, the number of mixture components should be determined. To select the number of the Gaussians K_j^p, for the j^{th} training sequence, representing the p^{th} action, the Bayesian Information criterion (BIC) (Bishop, 2006) is used. Thus, when EM converges the cluster labels of the motion curves are obtained. This is schematically depicted in Figure 1, where a set of motion trajectories, representing a certain action (e.g., p), in a video sequence (e.g., labeled by j) is clustered by a GMM into $K_j^p = 2$ curves for action representation. Note that, a given action is generally represented by a varying number of mean trajectories as the BIC criterion may result in a different number of components in different sequences.

2.4 Matching of Motion Curves

Once a new probe video is presented, where we must recognize the action depicted, the optical flow is computed, motion trajectories are created and clustered, and they are compared with the learned mean trajectories of the training set. Recall that human actions are not uniform sequences in time, since different actors perform the same action in different manner and at different speeds. This means that motion curves have varied lengths. An optimal matching may be performed using dynamic programming which detects similar pairs of curve segments. The longest common subsequence (LCSS) (Vlachos et al., 2002) is robust to noise and provides a similarity measure between motion trajectories since not all points need to be matched.

Let $c_1(t)$, $t \in [0,T]$ and $c_2(t')$, $t' \in [0,T']$ be two curves of different lengths. Then, we define the affin-

ity between the two curves as:

$$\alpha\left(c_1(t),c_2(t')\right)=\frac{LCSS\left(c_1(t),c_2(t')\right)}{\min(T,T')}, \quad (1)$$

where the $LCSS\left(c_1(t),c_2(t')\right)$ (Eq. (2)) indicates the quality of the matching between the curves $c_1(t)$ and $c_2(t')$ and measures the number of the matching points between two curves of different lengths. Note that the LCSS is a modification of the edit distance (Theodoridis and Koutroumbas, 2008) and its value is computed within a constant time window δ and a constant amplitude ε, that control the matching thresholds. The terms $c_1(t)^{T_t}$ and $c_2(t')_{t'}^{T'}$ denote the number of curve points up to time t and t', accordingly. The idea is to match segments of curves by performing time stretching so that segments that lie close to each other (their temporal coordinates are within δ) can be matched if their amplitudes differ at most by ε.

When a probe video sequence is presented, its motion trajectories are clustered using GMMs of various numbers of components using the EM algorithm. The BIC criterion is employed to determine the optimal value of the number of Gaussians K, which represent the action. Thus, we have a set of K mean trajectories y_k, $k=1,\ldots,K$ modeling the probe action.

Recognition of the action present in the probe video sequence is performed by assigning the probe action to the action of the labeled sequence which is most similar. As both the probe sequence y and the j^{th} labeled sequence of the p^{th} action in the training set x_j^p are represented by a number of GMM components, the overall distance between them is computed by:

$$d(x_j^p,y)=\sum_{k=1}^{K_j^p}\sum_{\ell=1}^{K}\pi_{jk}^p\pi_\ell\left[1-\alpha\left(x_{jk}^p(t),y_\ell(t')\right)\right], \quad (3)$$

where π_{jk}^p and π_ℓ are the GMM mixing proportions for the labeled and probe sequence, respectively, that is $\sum_k\pi_{jk}^p=1$ and $\sum_\ell\pi_\ell=1$. The probe sequence y is categorized with respect to its minimum distance from an already learned action:

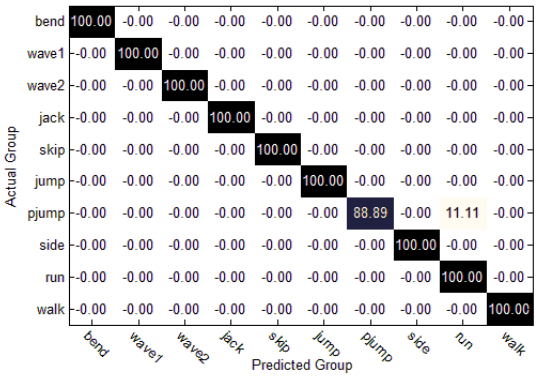
$$[j^*,p^*]=\arg\min_{j,p} d(x_j^p,y). \quad (4)$$

3 EXPERIMENTAL RESULTS

We evaluated the proposed method on action recognition by conducting a set of experiments over publicly available datasets. At first we applied the algorithm to the Weizmann human action dataset (Blank et al., 2005). The Weizmann dataset is a collection of 90 low-resolution videos, which consists of 10 different actions such as run, walk, skip, jumping jack, jump forward, jump in place, gallop sideways, wave with two hands, wave with one hand, and bend, performed by nine different people. The videos were acquired with a static camera and contain uncluttered background.

To test the proposed method on action recognition we adopted the leave-one-out scheme. We learned the model parameters from the videos of eight subjects and tested the recognition results on the remaining video set. The procedure was repeated for all sets of video sequences and the final result is the average of the individual results. The optimal number of mixture components K_j^p for the j^{th} video sequence, $j=1,\ldots,S_p$ of the p^{th} action $p=1,\ldots,A$ is found by employing the BIC criterion. The value of BIC was computed for $K_j^p=1$ to 10.

In the recognition step, in our implementation of the LCSS (2), the constants δ and ε were estimated using cross validation. Parameter δ, was set to 1% of the trajectories' lengths, and parameter ε was determined as the smallest standard deviation of the two trajectories to be compared. As shown in Table 1, the average correct classification of the algorithm on this dataset is 98.8%. The performances of other state-of-the-art methods on the same dataset are shown in Table 1. As it can be observed, we achieve better results with respect to four out of seven state-of-the-art methods. However, the proposed method provided only one erroneous categorization as one *jump-in-place* (pjump) action was wrongly categorized as *run*. It seems that in this case the number of Gaussian components K_j^p computed by the BIC criterion was not optimal. Figure 2 depicts the confusion matrix for this experiment.



Weizmann database, accuracy = 98.8%

Figure 2: Confusion matrix for the classification results for the Weizmann dataset for the estimation of the number of components using the BIC criterion for both the training and probe sequences.

$$LCSS\left(c_1(t),c_2(t')\right)=\begin{cases}0, \text{ if } T=0 \text{ or } T'=0,\\ 1+LCSS\left(c_1(t)^{T_t-1},c_2(t')^{T'_{t'}-1}\right), \text{ if } |c_1(t)-c_2(t')|<\varepsilon \text{ and } |T-T'|<\delta,\\ \max\left\{LCSS\left(c_1(t)^{T_t-1},c_2(t')^{T'_{t'}}\right), LCSS\left(c_1(t)^{T_t},c_2(t')^{T'_{t'}-1}\right)\right\}, \text{otherwise}\end{cases} \quad (2)$$

Table 1: Recognition accuracy and execution time over the Weizmann dataset. The results of (Blank et al., 2005; Seo and Milanfar, 2011; Niebles et al., 2008; Chaudhry et al., 2009; Lin et al., 2009; Jhuang et al., 2007; Fathi and Mori, 2008) are taken from the original papers.

Method	Accuracy (%)
Proposed Method	98 .8
(Blank et al., 2005)	100.0
(Chaudhry et al., 2009)	95 .7
(Fathi and Mori, 2008)	100.0
(Jhuang et al., 2007)	98 .8
(Lin et al., 2009)	100.0
(Niebles et al., 2008)	90 .0
(Seo and Milanfar, 2011)	97 .5

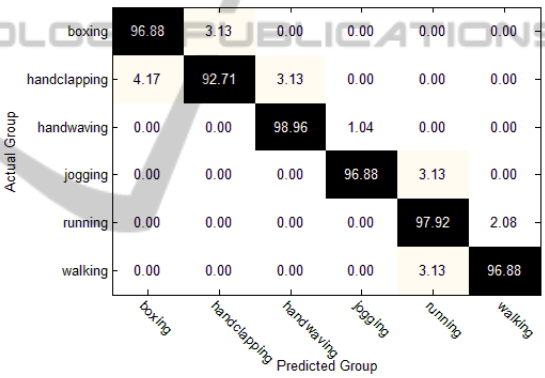
We have further assessed the performance rate of our method by conducting experiments on the KTH dataset (Schuldt et al., 2004). This dataset consists of 2391 sequences and contains six types of human actions such as walking, jogging, running, boxing, hand waving, and hand clapping. These actions are repeatedly performed by 25 different people in four different environments: outdoors (s1), outdoors with scale variation (s2), outdoors with different clothes (s3), and indoors (s4). The video sequences were acquired using a static camera and include a uniform background. The average length of the video sequences is four seconds, while they were downsampled to the spatial resolution of 160×120 pixels.

We tested the action recognition capability of the proposed method by using a leave-one-out cross validation approach. Accordingly, we learned the model from the videos of 24 subjects while we tested the algorithm on the remaining subject and averaged the recognition results. The confusion matrix over the KTH dataset for this leave-one-out approach is depicted in Figure 3. We achieved a recognition rate of 96.71%, which to the best of our knowledge is a very high performance for this dataset. In addition, comparison of the proposed method with other state-of-the-art methods is reported in Table 2. As can be observed, the proposed method provides the more accurate recognition rates. The proposed method attains high action classification accuracy as the BIC criterion determines the optimal value of Gaussians K_j^p for this dataset.

The average recognition time depends on the value of Gaussians K_j^p and it is approximately 2 sec for both datasets, on a standard PC (dual core, 2 GHz RAM).

Table 2: Recognition results over the KTH dataset. The results of (Fathi and Mori, 2008; Jhuang et al., 2007; Lin et al., 2009; Niebles et al., 2008; Schuldt et al., 2004; Seo and Milanfar, 2011) are taken from the original papers.

Method	Accuracy (%)
Proposed Method	96.71
(Fathi and Mori, 2008)	90.5
(Jhuang et al., 2007)	90.5
(Lin et al., 2009)	95.77
(Niebles et al., 2008)	83.33
(Schuldt et al., 2004)	71.72
(Seo and Milanfar, 2011)	95.1



KTH database, accuracy = 96.71%

Figure 3: Confusion matrix for the classification results for the KTH dataset for the estimation of the number of components using the BIC criterion for both the training and probe sequences.

4 CONCLUSIONS

In this paper, we presented an action recognition approach, where actions are represented by a set of motion curves assumed to be generated by a probabilistic model. The performance of the extracted motion curves is interpreted by discovering similarities between the motion trajectories, followed by a classification scheme. Although a perfect recognition performance is accomplished with a fixed number of Gaus-

sian mixtures, there are still some open issues in feature representation. Our next step is to apply this work to other benchmark databases with richer motion variations and more information to be modeled by a Gaussian mixture where more Gaussian components would be necessary. Moreover, an extension of the action classification method is envisioned in order to integrate it into a complete scheme consisting of motion detection, background subtraction, and action recognition in natural and cluttered environments, which is a difficult and more challenging topic.

REFERENCES

Aggarwal, J. K. and Ryoo, M. S. (2011). Human activity analysis: A review. *ACM Compututing Surveys*, 43(3):1–43.

Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

Blank, M., Gorelick, L., Shechtman, E., Irani, M., and Basri, R. (2005). Actions as space-time shapes. In *Proc.* 10th *IEEE International Conference on Computer Vision*, pages 1395–1402, Beiging, China.

Chaudhry, R., Ravichandran, A., Hager, G. D., and Vidal, R. (2009). Histograms of oriented optical flow and Binet-Cauchy kernels on nonlinear dynamical systems for the recognition of human actions. In *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1932–1939, Miami, Florida, USA.

Dollár, P., Rabaud, V., Cottrell, G., and Belongie, S. (2005). Behavior recognition via sparse spatio-temporal features. In *Proc.* 14th *International Conference on Computer Communications and Networks*, pages 65–72, Beijing, China.

Efros, A. A., Berg, A. C., Mori, G., and Malik, J. (2003). Recognizing action at a distance. In *Proc.* 9th *IEEE International Conference on Computer Vision*, volume 2, pages 726–733, Nice, France.

Fathi, A. and Mori, G. (2008). Action recognition by learning mid-level motion features. In *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1–8, Anchorage, Alaska, USA.

Gorelick, L., Blank, M., Shechtman, E., Irani, M., and Basri, R. (2007). Actions as space-time shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(12):2247–2253.

Jhuang, H., Serre, T., Wolf, L., and Poggio, T. (2007). A biologically inspired system for action recognition. In *Proc. IEEE International Conference on Computer Vision*, pages 1–8, Rio de Janeiro, Brazil.

Lin, Z., Jiang, Z., and Davis, L. S. (2009). Recognizing actions by shape-motion prototype trees. In *Proc. IEEE International Conference on Computer Vision*, pages 444–451, Miami, Florida, USA.

Lucas, B. D. and Kanade, T. (1981). An iterative image registration technique with an application to stereo vision. In *Proc.* 7th *International Joint Conference on Artificial Intelligence*, pages 674–679, Nice, France.

Morris, B. T. and Trivedi, M. M. (2011). Trajectory learning for activity understanding: Unsupervised, multilevel, and long-term adaptive approach. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(11):2287–2301.

Niebles, J. C., Wang, H., and Fei-Fei, L. (2008). Unsupervised learning of human action categories using spatial-temporal words. *International Journal of Computer Vision*, 79(3):299–318.

Poppe, R. (2010). A survey on vision-based human action recognition. *Image and Vision Computing*, 28(6):976–990.

Schindler, K. and Gool, L. V. (2008). Action snippets: How many frames does human action recognition require? pages 1–8, Anchorage, Alaska, USA.

Schuldt, C., Laptev, I., and Caputo, B. (2004). Recognizing human actions: A local SVM approach. In *Proc.* 17th *International Conference on Pattern Recognition*, pages 32–36, Cambridge, UK.

Seo, H. J. and Milanfar, P. (2011). Action recognition from one example. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(5):867–882.

Theodoridis, S. and Koutroumbas, K. (2008). *Pattern Recognition*. Academic Press, 4th edition.

Vlachos, M., Gunopoulos, D., and Kollios, G. (2002). Discovering similar multidimensional trajectories. In *Proc.* 18th *International Conference on Data Engineering*, pages 673–682, San Jose, California, USA.

Wang, Y. and Mori, G. (2011). Hidden part models for human action recognition: Probabilistic versus max margin. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 33(7):1310–1323.

Yan, X. and Luo, Y. (2012). Recognizing human actions using a new descriptor based on spatial-temporal interest points and weighted-output classifier. *Neurocomputing*, 87:51–61.

Yao, A., Gall, J., and Gool, L. V. (2010). A Hough transform-based voting framework for action recognition. In *Proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 2061–2068, San Francisco, CA, USA.