

Fig. 1 Sample frames from our behavior database (25 fps): three frames sampled by every six frames are used to characterize actions (walking) a A normal behavior of walking b same person but with a diverse appearance c a different person with a different velocity; d action captured from a different viewpoint; e moving cameras and dynamic backgrounds f multiple active subjects with occlusions

introduce "Gentle Adaboost" into our framework for more challenging situations, i.e., it requires analyzing the histogram-based feature selection, and to learn models on the spatio-temporal configuration between different cuboids in proposed three kinds of histograms. In turn, we use the standard window scanning technique and apply the learned classifiers onto the densely sampled rectangular sub-windows (i.e., cubic spatio-temporal volumes) within video sequences for the detection.

The rest of this paper is organized as follows. Section 2 summarizes the related work. Section 3 details feature design and representation for human actions using local motion histograms. Section 4 describes how we learn models on action classification histogram-based features using a boosting framework. Section 5 illustrates our experimental settings and presents experimental results on several video sequences. Section 6 concludes this paper.

2 Related work

Recently, there has been significant interest in approaches that address human action detection. Many previous approaches for behavior recognition were based on tracking models [17, 19, 22], which apply tracked motion trajectories of body parts to action recognition. In this case, an accurate rate segmentation of subjects from backgrounds is assumed beforehand. Consequently, the robustness of the algorithm is highly dependent on the segmenting and tracking system. The authors in [5] have reviewed the previous work on activity recognition, most of which involve tracking body parts segmented from the static background.

Another class of approaches performs recognition by using sparsely detected spatio-temporal features. Schuldt et al. [11, 18] devise spatio-temporal feature detectors on Harris corners in 3D case, and Dollár et al. [1] design the detectors from local maxima of the response function defined by separable linear filters. Although these approaches indicate good potentials, they pose a problem toward handling

Local motion histograms We focus on spatio-temporal volume analysis for human action detection due to its simplicity and effectiveness. Thus the key problem is to characterize actions within volumes by some kinds of features.

3.1 Feature design

Feature design is a significant problem because informative features capture the essence of a behavior pattern which facilitates our task of detection. Our idea for feature design is derived from three considerations:

1. It is believed that most of the information salient to recognizing action can be captured from the optical flow, and the appearance of object is less relevant, which includes colors and textures, etc.

Fig. 2 Spatio-temporal unit: basic blocks

- Using histogram-based image descriptors has achieved a remarkable success in object detection on static images among the vast variety of existing approaches, and the Histogram of Oriented Gradient (HOG) has been proved effective to describe appearance.
- To simplify the problem, most existing work assumes that the camera and the background are essentially stationary. In our case, we make efforts to design a detector that could analyze activities where the camera or the background moves around in the scenes.

$$M(u, v) = |(u, v)| \tag{2}$$

Based on the above considerations, we make some attempts as follows:

- We do not combine any appearance descriptors directly into behavior representation, but focus on motion features and make full use of optical flow vectors as descriptors.
- Local histograms provide effective means to represent visual information. Besides strong descriptive power, invariant to noise or affine transformation and spatially unordered, they have a good property for densely sampled description that all histograms can be efficiently calculated by using an integral histograms technique [15]. We use the similar idea as HOG to define local motion histograms.
- It is noticeable that local motion histograms can be built up from both differentials of optical flow and absolute optical flow orientation. The former description tends to describe relative motion between different parts against moving backgrounds.

To make behavior representation tractable, we define local motion histograms by means of optical flow for capturing motion independent of appearance. To reduce the computational requirements of detection task, we iterate the calculation of integral histograms on the base of volumetric basic blocks rather than pixel points. The term of basic block refers to a spatio-temporal region at a spatio-temporal location (x, y, t) with a small size (dx, dy, dt) , which is defined as an aggregate

$$B = \{ p | x^{(p)} < x + dx, y^{(p)} < y + dy, t^{(p)} < t + dt \} \tag{1}$$

where p denotes a pixel point at location $(x^{(p)}, y^{(p)}, t^{(p)})$.

$$\theta(u, v) = \arg \max_{i \in [0, 7]} \left(u \cos\left(\frac{i\pi}{4}\right) + v \sin\left(\frac{i\pi}{4}\right) \right) \tag{3}$$

where (u, v) stands for a 2D vector, and $\theta(u, v)$ optimizes the projection: $\cos(\arctan(u, v)) \sin(\frac{i\pi}{4})$.

Intra-block absolute histogram (IAH) When cameras and backgrounds are largely stationary, the original optical flow is sufficient to describe those absolute motions caused by actions of subjects. Even when there exist some camera operations (pan, tilt, or zoom), the original optical flow is still a good clue for discovering salient motions. In this case, we employ the magnitude and orientation calculated by using an optical flow vector (U, V) at each sample pixel in a basic block to represent its inside behavior. If magnitudes are taken as weights and orientations are used for angular voting, orientation histograms are created as a descriptor to characterize distributions of optical flow. As shown in Fig. 3a, each histogram is arranged in eight discrete directions, whose bins denote the sum of all contributions along the current direction, shown as the length of arrows. Since the eight-bin histogram accumulates all absolute motions inside a block, we call the resulting descriptor as intra-block absolute histogram (IAH). IAH for a given basic block B is formulated as

$$IAH(i) = C \sum_{p \in B} M(U^{(p)}, V^{(p)}) \delta[i - \theta(U^{(p)}, V^{(p)})] \tag{4}$$

$$C = \frac{1}{\sum_{p \in B} M(U^{(p)}, V^{(p)})} \tag{5}$$

where $i = 0, 1, \dots, 7$ is the bin index and δ is the Kronecker delta function. The normalization constant is imposing the condition $\sum_{i=0}^7 IAH(i) = 1$.

$$NDH^V(i) = C^V \sum_{p \in B} M(V_x^{(p)}, V_y^{(p)}) \delta[i \check{S} O(V_x^{(p)}, V_y^{(p)})] \quad (7)$$

where C^U and C^V are both normalization constants.

Inter-block differential histogram (IDH). The differentials mentioned in the above are calculated from neighboring points, which usually outstands motion boundaries. In order to capture the relative motion of body parts, we exploit inter-block flow differentials. This means we compute flow differentials across neighboring basic blocks. This type of differentials is naturally capable to compensate most effects of global motions caused by camera operations as well. Figure 3c depicts how the differentials are computed.

Since the spatial displacement (dx, dy) between basic blocks are relatively large and dx is not essentially equal to dy , new histograms are encoded (U_x, V_x) and (U_y, V_y) . They are respectively, taken as pairs for orientation calculation and angular voting. The resulting descriptors consisting of two channels of eight-bin histograms are called as inter-block differential histogram (IDH). Similarly, they are formulated as

$$IDH^X(i) = C^X \sum_{p \in B} M(U_x^{(p)}, V_x^{(p)}) \delta[i \check{S} O(U_x^{(p)}, V_x^{(p)})] \quad (8)$$

$$IDH^Y(i) = C^Y \sum_{p \in B} M(U_y^{(p)}, V_y^{(p)}) \delta[i \check{S} O(U_y^{(p)}, V_y^{(p)})] \quad (9)$$

where C^X and C^Y are both normalization constants. It is worth noting that the gradients $U_x, U_y, V_x,$ and V_y for IDH are computed in a different way from those for NDH although the same symbols are used.

Our proposed local motion histograms bear some similarity to Dalal's motion descriptors, [24], where differentials of optical flow are employed. However, there exists some substantial distinct between them. Firstly, our proposed descriptors are spatio-temporal volumetric features and the histograms are accumulated in the normalized action cuboids. Secondly, the defined IDH is simpler than Dalal's internal motion histograms (IMH), which are calculated over basic blocks and only two neighboring blocks are involved rather than eight outer cells. Finally, both absolute values and differentials are used for behavior representation, and NDH and IDH are organized together as complementary features for IAH, not alternative features for each other.

3.2 Behavior representation

Using basic blocks as the elementary unit, we denote any behavior region by grouping adjacent basic blocks into a large spatio-temporal volume. To depict its inside action, the volume is divided into sub-regions with different sizes at different positions. Moreover, to reserve some spatial or

Fig. 3 Local motion histograms of a plane inside basic blocks. a IAH is based on (U, V) ; b NDH is based on (U_x, U_y) or (V_x, V_y) ; c IDH is based on (U_x, V_x) or (U_y, V_y)

Neighbor-point differential histogram (NDH). Obviously, local differential of optical flow cancels out most effects of camera motion, such as pan and tilt, which can even reduce the effects incurred by zoom and rotation. Usually, the differentials are maximal at motion boundaries between a stationary region and a motional one, or two motional regions, which coincide with limb and body edges for human subjects with a behavior of walking or running. In some sense, flow differentials possess some character like edge-based descriptors.

We encode a type of local motion histogram to capture the local orientations of motion boundaries in a simple way. The two flow components U, V are regarded as independent features. Taking local gradients (U_x, U_y) and (V_x, V_y) separately and calculating the corresponding gradient magnitudes and orientations (see Fig. 3b), we obtain weighted votes into local orientation histograms, which results two channels of eight-bin histograms. This resulting descriptors are called as neighbor-point differential histogram (NDH). Similar to the above defined IAH, they are formulated as

$$NDH^U(i) = C^U \sum_{p \in B} M(U_x^{(p)}, U_y^{(p)}) \delta[i \check{S} O(U_x^{(p)}, U_y^{(p)})] \quad (6)$$

Fig. 4 Four different arrangements of basic blocks

temporal information within a sub-region, the histograms are calculated with different arrangements of basic blocks (see Fig.4), and are respectively, concatenated into a single feature vector.

The 3-channel histograms (NDH, NDHx2, IDHx2) under four arrangements with different regional sizes at different positions are calculated separately, then a dense representation for an action is built up. This representation leads to a histogram set with a huge size, which makes it impossible to be used for detecting directly. It is essential to filter the resulting descriptors and find those representative and discriminative features to characterize an action. Section 4 will discuss this in details.

There are two pending problems. One is parameter tuning for calculation of histograms. Basic blocks are given the size of $dx, dy = (4, 5, 6)$, $dt = (3, 4, 5)$, and the normalized action volumes have different numbers of units dependent on action types. The other is optical flow estimation, which is important for building up descriptors. Since optical flow

depends on the temporal and spatial resolution, it is computed on the original resolution and then scaled.

However, dense optical flow between two consecutive frames is known as a coarse feature, which is noisy and unreliable. Moreover, some methods are going together with local aperture effects. The local gradient (U_x, U_y, V_x, V_y) are used to accumulate the histograms, thus smooth and accurate flow are preferable for NDH and IDH. Based on these considerations, our initial efforts concentrated on some global methods, especially multi-scale non-linear diffusion based algorithm [16], and high-quality results are desired.

Based on the later boosting framework, we compared the performance of this optical flow estimation with different methods on a dataset described later in this paper. Results are shown in Fig.5. Almost a same conclusion is drawn as Proesmans's flow does not provide improved performance while it is computationally expensive. It is over-smoothed which tends to blur the motion boundaries, and in turn, reduces the descriptive power of NDH and IDH. In contrast, Horn's flow is fast to be calculated and preserves the motion boundaries well, which keeps more number of selected features for NDH and IDH, but the final performance does not be promoted apparently. Our explanation is that Horn's flow is noisy on some pixels (e.g., spatio-temporal corners), whose U and V get unexpected big values and make histograms unstable. Gennert's flow relaxes the brightness constant assumption, which sounds appropriate to our framework. In fact,

Fig. 5 Comparison of detecting performance by histograms from various optical flow estimations on KTH dataset. a Precision-Recall curves for detecting 'walking' action (real mode); b number of selected features of a; c precision-Recall curves for detecting 'boxing' action (real mode); d number of selected features of c. In b and d the total number of features are both 50

it obtains a stable flow field, but it naturally outstands the moving boundary and despises inner flow. As a result, it selects relatively less number of NDH and IDH. This method working with our framework leads to the worst performance.

A saturated Horn-Os flow (S-Horn) is introduced into computing motion descriptors, which originates from very simple idea: the magnitude of Horn-Os motion vector is saturated by its neighbors, if $M(u, v) > \frac{\gamma}{8} \sum_{i=0}^7 M_i(u, v)$, where γ is a experiential factor ($\gamma = 3$ is recommended). It is amazing that such a small modification enhances the performance apparently. This flow will be used to compute histograms in all the later experiments.

4 Learning models for histogram-based features

Given a video database involving human actions with labeled positive and negative samples, we are required to classify or detect behaviors in a novel sequence. As outlined above, we first construct local motion histograms for behavior representation.

A naive, nevertheless simple method for classification is to find the best match to the querying motion descriptor, which can be performed in a KNN framework. In such a case, we must provide an appropriate similarity measure for our proposed motion descriptors. This is really difficult problem for our method because our descriptor set is composed of several types of histograms, and it is hard to give the weights for them. In addition, the dense representation leads to a large number of features, which makes the computational cost expensive.

Learning discriminative action models for boosting classifiers does not need any form of similarity measure, but does well in good feature selection. It is also a promising approach to handle the variation within an action category. However, most existing boosting frameworks have been employed to select one-dimensional features, such as Haar-like features, where an efficient classifier can be found by selecting an optimal decision threshold. Our histogram-based descriptors are multi-dimensional features with different types and different arrangements, it is difficult to find a proper decision threshold.

In this paper, linear projection technique is utilized to deal with histogram-based features. The classification task is not directly converted from a multi-dimensional problem to a one-dimensional one, but weak classifiers for boosting are learned on unprocessed histograms via this technique. During the learning process, Gentle AdaBoost will be employed as a strong learner to select the position, the size, the type, and the arrangement of our local descriptors in action volumes. The only criterion is to minimize the training error for the samples.

4.1 Boosting framework

Generally, boosting provides a simple way to approximate additive models of the form

$$H(x) = \sum_{m=1}^M \beta_m h_m(x) \tag{10}$$

where $H(x)$ is called as a strong learner or is the input feature vector with a class label $\{+1, -1\}$, and M is the number of boosting rounds. The functions $h_m(x)$, also written as $b(x; \gamma_m)$, are base classifiers which are usually simple functions of x . The expansion coefficients β_m and the parameters γ_m are jointly fit to training data in a forward stage-wise manner.

All AdaBoost-based techniques can be considered as a greedy optimization method for minimizing exponential error function

$$J[H(x)] = E(e^{\tilde{S}y \cdot H(x)}) \tag{11}$$

where the term $H(x)$ is related to the generalization error (out-of-sample error rate), and called as \tilde{O} margin \tilde{O} .

For binary classification problems, there are two versions of the most commonly used AdaBoost procedures: One is \tilde{O} Discrete Adaboost \tilde{O} , where each $h_m(x)$ is a classifier producing values $\{+1, -1\}$ and β_m are constants, the corresponding prediction is $\text{sign}(H(x))$. The other is \tilde{O} Real Adaboost \tilde{O} , where real-valued predictions $h_m(x)$ are combined with β_m and absorbed in Eq. (10) with a simpler form. The sign of each $h_m(x)$ gives the classification, and the value of each $|\beta_m h_m(x)|$ is a measure of the \tilde{O} confidence \tilde{O} in the prediction.

Gentle AdaBoost (GAB) is a more robust and stable version of real AdaBoost [4], which has ever been the most practically efficient boosting algorithm used in object detector [13]. In this paper Gentle AdaBoost is used to select our histogram-based features.

Gentle AdaBoost takes adaptive Newton steps to minimize error $J[H(x) + h_m(x)]$ by

$$H(x) \rightarrow H(x) + \frac{E[e^{\tilde{S}yH(x)} y | x]}{E[e^{\tilde{S}yH(x)} | x]} = H(x) + E_w(y|x). \tag{12}$$

Equivalently, the weak hypothesis is written as

$$h_m(x) = E_w(y|x). \tag{13}$$

Here $E_w(\cdot|x)$ refers to a weighted conditional expectation. The weight $w(x, y) = e^{\tilde{S}yH(x)}$ is updated by

$$w(x, y) \rightarrow w(x, y)e^{\tilde{S}yh_m(x)}. \tag{14}$$

To get optimized $h_m(x)$, we expand $J[H(x) + h_m(x)]$ to the second order about $h_m(x) = 0$. Minimizing pointwise with respect to $h_m(x)$, there is

$$\hat{h}_m(x) = \arg \min_{h_m} (E_w[(y - \tilde{S}h_m(x))^2 | x]) \tag{15}$$

which gives the way to select a trained base classifier and produce a weak classification rule.

4.2 Weak learner

Although Adaboost doesn't have strict requirement for the choice of weak learners, effective weak learners tends to enhance the performance of the final classifier. Available weak learners are usually Classification and Regression Trees (CART). Whereas, motivated by Laptev's work [10], we use Weighted Fischer Linear Discriminant (WFLD) as a weak learner for multi-valued histogram features, where multi-dimensional features are projected onto a pre-defined set of one-dimensional manifolds using a fixed set of functions. The weak learner is defined as

$$h(x) = w^T x + b, \quad \text{with } w = (S_1 + S_2)^{-1}(\mu_1 - \mu_2) \quad (16)$$

where μ_1, μ_2 stand for the weighted class means and S_1, S_2 for the weighted class covariance matrices, and the threshold obtained by projecting total means with a negative w . Given the weights $\{w_i\}$ corresponding to samples $\{x_i\}$, the matrices have the form

$$\mu = \frac{1}{n \cdot \sum w_i} \sum_i w_i f(z_i) \quad (17)$$

$$S = \frac{1}{(n-1) \cdot \sum w_i^2} \sum_i w_i^2 (f(z_i) - \mu)(f(z_i) - \mu)^T. \quad (18)$$

WFLD seeks for finding the optimized projecting directions which are efficient for discrimination. The resulting linear projection transformation yields the maximum ratio of between-class scatter to within-class scatter for weighted samples. In comparison with CART, each trained WFLD produces a more compact classification rule, which leads to a more efficient boosting classifier.

4.3 Feature selection with GAB + WFLD

As mentioned before, the proposed three-channel histograms (IAH \times 1, NDH \times 2, IDH \times 2) build up a dense representation for an action with a huge histogram set. Intuitively, each kind of feature delivers different data semantics for an action. However, it keeps unknown whether they indeed carry a different amount of discriminative information for an action classification. Using the GAB+WFLD algorithm, feature selection is used to explore the useful histograms for our application.

To understand the added value of these introduced descriptors, results are reported separately for different features and in combination with each other. Table 1 and 2 list the performance independently. From the two tables, the best

Table 1 Accuracy (%) of different feature combinations for detecting Walking (lite mode) on the KTH dataset

Number of features	1	5	10	20	35	55	80
IAH	27	45	51	50	54	57	57
NDH	42	53	57	63	65	69	69
IDH	40	52	59	67	69	71	71
IAH + NDH	35	57	80	89	91	93	94
NDH + IDH	44	65	76	87	90	95	95
IAH + IDH	40	63	84	86	91	92	91
IAH + NDH + IDH	51	69	88	90	92	96	97

Table 2 Accuracy (%) of different feature combinations for detecting Boxing (lite mode) on the KTH dataset

Number of features	1	5	10	20	35	55	80
IAH	18	35	42	39	44	44	43
NDH	31	52	56	56	55	56	56
IDH	37	54	65	67	67	67	67
IAH + NDH	31	42	54	70	79	79	79
NDH + IDH	39	62	72	85	91	91	92
IAH + IDH	38	57	68	82	89	87	88
IAH + NDH + IDH	39	65	77	87	91	95	95

accuracies of detection are obtained by about 50 features. For each individual feature, it reaches the best accuracy within 30 features.

The two actions involving in these comparisons hold different moving nature, Walking action has a relatively stable moving region, and bears relative motions between body parts, while most Boxing actions have a largely stationary region, the actions focus on the movement from hands. The results in the two tables coincide with our intuition that IDH shows great importance on catching motions between parts, and in most cases, NDH working with IDH achieves a satisfactory performance without need of IAH, especially when the moving region has a large size or with simple motions on the 2D plane.

5 Experiments

5.1 Datasets

To evaluate the performance of the proposed method, we conducted experiments on three different datasets: Facial Expression dataset (FE3) [KTH human activity dataset (KTH) [18], and Drinking and Smoking dataset (D&S) [2].

They are all publicly available online, and some sample images from them are shown in Fig. 6.

The face data in the FE dataset involves two subjects, each expressing six emotions under two lighting setups. Under

Fig. 6 Sample images from some public datasets

each lighting setup, each individual was asked to repeat six different expressions eight times. The expressions are anger, disgust, fear, joy, sadness and surprise. The subject always start with a neutral express, expresses an emotion, and return to neutral, all in about 60 frames.

The human action data from the KTH dataset contains 25 individuals, each engaged in the following activities: walking, jogging, running, boxing, hand clapping, and hand waving. Each person repeats the six actions in each of four scenarios: outdoor, outdoor with camera zooming, outdoor

wearing different clothes, indoor. And their durations are normalized with same spatial size but different temporal lengths, and our detectors will learn to generalize the noisy

The D&S dataset consists of annotations for two action durations of actions. The first set of experiments examines our method's ability and Cigarettes (2003), Sea of love (1989) and in the drinking sequence recorded by INRIA/Vista. In contrast to most existing datasets, the actions in this dataset are not recorded in a controlled or simplified setting with simple backgrounds, but in comprehensive and realistic scenes with different subjects and from different view points. Although the two kinds of different illuminations; (2) different subjects under the same actions are atomic actions with a reasonable well-defined structure in time, the annotated samples possess large variability of scales, locations, and surroundings.

5.2 Training and testing settings

When annotating all training samples for detection it is extremely important to align them in both spatial and temporal domains. Similar to the well-annotated D&S dataset, we discretize those original coarse frame-based annotations for the KTH dataset, and manually segment their action instances to a fine degree for training. In the spatial domain, actions are labeled by rectangles or squares which keep the subject in the middle-center (boxing, hand clapping, etc.) or cover the active regions (walking, running, etc.). In the temporal domain, all sorts of actions are defined to start at the same phrase, and end at the same phrase as well (see Fig. 7). Even more, we split periodic actions in the KTH dataset into non-periodic actions (i.e., atomic actions), which considerably simplifies the annotation with temporal alignment.

Besides alignment, normalization on all training samples is another key technique when training our detectors. In the spatial domain, each frame from a given action volume is resized into a preset size by interpolation on pixels. In most cases, redundant regions or blanks are added in order to maintain aspect ratios. Furthermore, temporal interpolation is utilized in our method because behavioral durations are good features for action description. In this way, the action volumes

Fig. 7 Frames from two hand clapping actions after spatial and temporal alignment. Top frames from #0 to #24 (dt = 24) constitute an action volume; bottom frames from #54 to #90 (dt = 36) constitute an action volume

Fig. 8 Results on the FE dataset compare with the best existing results; b confusion matrix for the same subject under different illuminations; c confusion matrix for different subjects under the same illumination; d confusion matrix for different subjects under different illuminations

drinking samples selected from all the video clips as positive samples, and for testing we scan three episodes containing 38 drinking actions. The training and the testing sets have overlap in subjects or scenes.

For the first set of experiments, we learn a multi-class model for the classifying problem on the FE dataset, and on the other hand, we train binary classifiers for the detecting task in the later two sets of experiments. In addition, around the annotated positive samples we choose random durations of clips at random positions with random scales to generate negative samples for training binary classifiers.

5.3 Results

For the FE dataset, we compare the overall classification rates with the best results of Dollár et al. in Fig. 8a. It is obvious that our method performs better under changes of

illuminations (case 2 and case 3). Furthermore, the confusion matrices on three testing sets are presented in Fig. 8b, d, which show large confusion between similar actions "anger" and "disgust".

For the KTH dataset we summarize the recognition rate through those detecting results, and give the confusion matrices for the two modes in Fig. 8c, d. It shows large confusion between "hand clapping" and "boxing", as well as "running" and "jogging". This is consistent with our intuition that those actions involve similar hand motions or similar leg motions. The results for the two modes depict that outdoor with camera zooming and indoor scenarios markedly degenerate our method's performance. A reasonable explanation is that various resolutions and changes of illuminations cause a considerable side effect in calculating optical flow.

Table 3 compares classifying accuracy with previous studies on the same dataset KTH. Since the experimental setting of most existing studies are not the same as ours, the results cannot be compared directly and the listing accuracies do not

Fig. 9 Results on the KTH dataset classification for walking actions, where the lighted boxes mark correct decisions by the walking detector and the darkened boxes mark false decision by jogging detector, several detections obtained by the hand waving detector, where the last two darkened boxes mean false detections for hand clapping; c, d confusion matrices for two testing modes

mean too much. For example, Kim's method has achieved classification, the accuracy obtained by our method is competitive. an impressive accuracy at 95%, but space-time alignment is not. For the D&S dataset we detect human actions in real actions is manually done. In fact, a more challenging work is done in this paper, where the classifying problem is realistic scenarios with variation in subjects and scenes, etc. ted as an automatic detecting problem of multiple actions. In Fig. 10b precision-recall curves and average precision from unsegmented testing sequences. Although our detection method does not specifically aim for whole sequence Demo video: <http://ccs.sjtu.edu.cn/673/3d3mh>

Table 3 Comparison of classifying accuracy on the KTH dataset

Related studies	Accuracy (%)
Our method (IAH + NDH + IDH)	85.1
Ke et al. [3]	63.0
Schuldt et al. [8]	71.7
Dollár et al. [3]	81.2
Niebles et al. [4]	81.5
Wong et al. [21] (pLSA-ISM)	83.9
Wong et al. [21] (WX-SVM)	91.6
Kim et al. [9]	95.3

cision, and our method tends to perform better in rejecting similar non-drinking actions.

From all above experiments, we observe that the combination of different motion descriptors plays an important role in action recognition. It is found that without any explicit appearance of shape information, human actions under clutter background or moving background can also be well characterized by the local motion histograms. At the same time, Gentle AdaBoost is proved to be powerful enough to select parameters for classifiers.

6 Conclusions

In this paper we addressed human action detection in realistic scenarios. Our method shows great potentials in action representation within a spatio-temporal volume. The extracted histogram-based descriptors act as complementary information for each other. The Gentle Adaboost framework working with WFLD is proved to be able to select discriminative histogram-based features and learn robust and efficient detectors.

Our method is tested in a number of experiments against well established algorithms, and all experimental tests show the satisfying results. Despite of different appearance, scale changes, clutter background or moving background, our results on classifying and detecting problems are comparable with the previous studies, or outperform the previous results.

The experimental results not only validate the effectiveness of our method, but also prove that without the support of appearance and shape information, only motion information is capable of describing human actions well. However, since we have not combined any appearance or shape descriptors with local motion histograms, it is unknown whether the combination will improve the performance. This is part of our future work.

References

1. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. *Comput. Vis. Pattern Recognit.* 1886-893 (2005)
2. Dalal, N., Triggs, B., Schmid, C.: Human detection using oriented histograms of flow and appearance. *Eur. Conf. Comput. Vis.* 428-441 (2006)
3. Dollár, P., Rabaud, V., Cottrell, G., Belongie, S.: Behavior recognition via sparse spatio-temporal features. In: *VS-PETS*, pp. 65-72 (2005)
4. Friedman, J., Hastie, T., Tibshirani, R.: Additive logistic regression: A statistical view of boosting. *Ann. Statist.* 337-374 (2000)
5. Gavrilin, D.M.: The visual analysis of human movement: A survey. *Comput. Vis. Image Understanding* 3(1), 82-98 (1999)
6. Gennert, M.A., Negahdaripour, S.: Relaxing the brightness constancy assumption in computing optical flow. *A.I. Memo*, p. 975. MIT Press, Cambridge (1987)

Fig. 10 Results on the D&S dataset: the first nine detections on the testing set obtained by our "drinking" detector, where the second box in the first row and the first box in the second row are false detections; b comparison of precision-recall curves in "drinking" action detection task

(AP) values illustrate the detecting performance on "drinking" action. Our method outperforms Laptev's best result [12] (OF5 with Keyframe priming) with a better average pre-

7. Horn, B.K., Schunck, B.G.: Determining optical flow. *Artif. Intell.* 17, 185-203 (1981)
 8. Ke, Y., Sukthankar, R., Hebert, M.: Efficient visual event detection using volumetric features. *IEEE Int. Conf. Comput. Vis.* 166-173 (2005)
 9. Kim, T.K., Wong, S.F., Cipolla, R.: Tensor canonical correlation analysis for action classification. In: *CVPR* (2007)
 10. Laptev, I.: Improvements of object detection using boosted histograms. In: *BMVC*, vol. 3, pp. 949-958 (2006)
 11. Laptev, I., Lindeberg, T.: Space-time interest points. *IEEE Int. Conf. Comput. Vis.* 1, 432-439 (2003)
 12. Laptev, I., Pžrez, P.: Retrieving actions in movies. *IEEE Int. Conf. Comput. Vis.*, pp. 432-439 (2007)
 13. Lienhart, R., Kuranov, A., Pisarevsky, V.: Empirical analysis of detection cascades of boosted classifiers for rapid object detection. MRL technical report (2002)
 14. Niebles, J.C., Wang, H., Li, F.F.: Unsupervised learning of human action categories using spatial-temporal words. In: *BMVC* (2006)
 15. Porikli, F.: Integral histogram: A fast way to extract histograms in cartesian spaces. *Comput. Vis. Pattern Recognition* 829-836 (2005)
 16. Proesmans, M., Gool, L.J.V., Pauwels, E.J., Oosterlinck, A.: Determination of optical flow and its discontinuities using non-linear diffusion. In: *European Conference on Computer Vision*, pp. 295-304. Springer, London (1994)
 17. Ramanan, D., Forsyth, D.A.: Automatic annotation of everyday movements. In: *Advances in Neural Information Processing Systems*, vol. 16. MIT Press, Cambridge (2004)
 18. Schuldt, C., Laptev, I., Caputo, B.: Recognizing human actions: A local svm approach. *Int. Conf. Pattern Recognition* 32-36 (2004)
 19. Shah, M., Jain, R.: *Motion-Based Recognition. Computational Imaging and Vision Series.* Kluwer, Dordrecht (1997)
 20. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. *Comput. Vis. Pattern Recognition* 1151-1158 (2001)
 21. Wong, S.F., Kim, T.K., Cipolla, R.: Learning motion categories using both semantic and structural information. In: *CVPR* (2007)
 22. Yilmaz, A., Shah, M.: Recognizing human actions in videos acquired by uncalibrated moving cameras. *IEEE Int. Conf. Comput. Vis.* 1, 150-157 (2005)
- X. Kong received the B.S. and M.E. degrees in computer science and automation from Anhui University, China, in 2000 and 2004, respectively. Currently he is undertaking a Ph.D. degree at the Department of Electronic Engineering in Shanghai Jiaotong University, China. His research interests include content-based image retrieval, pattern recognition, image processing and intelligent video surveillance.
- G. Zeng received the B.S. and M.E. degrees in electronic engineering from Xidian University, China, in 1988 and 1991, respectively, and Ph.D. degrees from Shanghai opto-machine center, in 1997. From 1997 to 1999, he was a postdoctoral researcher at the State Key Laboratory of ISN in Xidian University, China. From 2001 to 2002, he was a research scientist in the University of Albert-Ludwigs Freiburg, Germany. Now he is a professor at the Department of Electronic Engineering in Shanghai Jiaotong University, China. His research interests include video content computing, indexing and security, quantum communication and quantum identity verification.
- J. Fan received the M.S. degree in theory physics from Northwestern University, Xian, China, in 1994 and the Ph.D. degree in optical storage and computer science from Shanghai Institute of Optics and Fine Mechanics, Chinese Academy of Sciences, Shanghai, China, in 1997. He was a Researcher at Fudan University, Shanghai, during 1998. From 1998 to 1999, he was a Researcher with Japan Society of Promotion of Science (JSPS), Department of Information System Engineering, Osaka University, Osaka, Japan. From September 1999 to 2001, he was a Researcher in the Department of Computer Science, Purdue University, West Lafayette, IN. In 2001, he joined the Department of Computer Science, University of North Carolina at Charlotte as an Assistant Professor and then became Associate Professor. His research interests include content-based image/video analysis, classification and retrieval, surveillance videos, and statistical machine learning.

Author biographies

Q. Luo received the B.S. and M.E. degrees in ship engineering from Wuhan University of Technology, China, in 2000 and 2003, respectively. Currently he is a Ph.D. candidate at the Department of Electronic Engineering in Shanghai Jiaotong University, China. His research interests include computer vision, video retrieval and video understanding. He is working on projects involving video surveillance, activity analysis in intelligent video systems.