Recognizing Actions Using Depth Motion Maps-based Histograms of Oriented Gradients

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ABSTRACT

In this paper, we propose an effective method to recognize human actions from sequences of depth maps, which provide additional body shape and motion information for action recognition. In our approach, we project depth maps onto three orthogonal planes and accumulate global activities through entire video sequences to generate the Depth Motion Maps (DMM). Histograms of Oriented Gradients (HOG) are then computed from DMM as the representation of an action video. The recognition results on Microsoft Research (MSR) Action3D dataset show that our approach significantly outperforms the state-of-the-art methods, although our representation is much more compact. In addition, we investigate how many frames are required in our framework to recognize actions on the MSR Action3D dataset. We observe that a short sub-sequence of 30-35 frames is sufficient to achieve comparable results to that operating on entire video sequences.

Categories and Subject Descriptors

I.4.9 [**Applications**]

General Terms

Algorithms, Performance, Experimentation

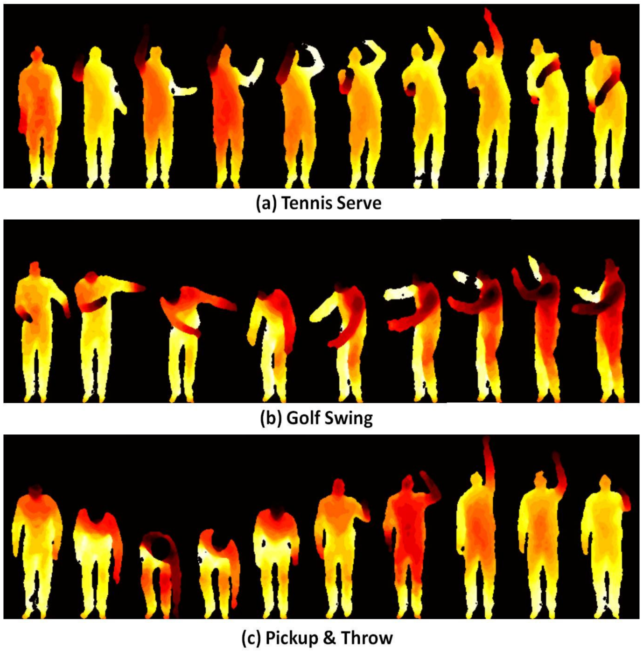
Keywords

Action Recognition, RGBD Camera, Depth Maps, Feature Representation

1. INTRODUCTION

Automatic human action recognition has many real-world applications including content-based video search, human-computer interaction, video surveillance, health care, and etc [7-9, 12-14]. In the past decades, research of human action recognition mainly concentrates on video sequences captured by traditional RGB cameras. The spatio-temporal volume-based methods have been extensively used for recognizing actions through measuring similarities between action volumes. In order to facilitate accurate similarity measurements, various detection and representation methods of spatio-temporal volumes have been proposed [3, 5-6]. The trajectory-based approaches have been explored for recognizing human activities as well [10]. In this case, human actions are interpreted by the movements of a set of key joints of human body. However, in traditional videos it is nontrivial to quickly and reliably detect and track human body joints.

As the imaging technique advances, e.g. the launch of Microsoft Kinect, it has become feasible to capture color image sequences as well as depth maps in real time by RGBD sensors. The depth maps are able to provide additional body shape and movement information to distinguish actions that generate similar projections from a single view, which motivates recent research work to explore action recognition based on depth maps. A Bag-of-3D-Points method was proposed in [7] to represent postures by sampling 3D points from depth maps. An action graph was then employed to model the sampled 3D points to perform action recognition. Their experimental results on MSR Action3D dataset [7, 15] validated the superiority of 3D silhouettes from depth maps over 2D silhouettes from a single view.


(a) Tennis Serve

(b) Golf Swing

(c) Pickup & Throw

Figure 1. The sampled sequences of depth maps for actions of (a) Tennis Serve, (b) Golf Swing, and (c) Pickup & Throw.

In this paper, we focus on recognizing human actions using sequences of depth maps. Fig. 1 illustrates the depth maps for actions *Tennis Serve*, *Golf Swing*, and *Pickup & Throw*. As shown in this figure, depth maps provide additional shape and motion information. However, depth maps also incur a great amount of

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data which might result in expensive computations. Here, we propose an effective and efficient approach to recognize human actions by extracting Histograms of Oriented Gradients (HOG) descriptors from Depth Motion Maps (DMM). The DMM are generated by stacking motion energy of depth maps projected onto three orthogonal Cartesian planes. The stacked motion energy of each action category produces specific appearances and shapes on DMM, which can be used to characterize corresponding action categories. Motivated by the success of HOG in human detection [2], we adopt HOG descriptors to represent DMM. Compared to the original depth data, the proposed DMM-HOG representation is more compact and more discriminative. We further explore how many frames are sufficient to perform action recognition using DMM-HOG. The experiments on MSR Action3D dataset [15] demonstrate that a short sub-sequence (e.g. 35 frames) is sufficient to obtain reasonably accurate recognition results for human action recognition. This observation is important to make online decisions and to reduce observational latency when humans interact with computers.

2. RELATED WORK

The spatio-temporal volume-based methods are widely used in action recognition from videos captured by traditional RGB camera. These approaches mainly focus on detection and representation of space-time volumes. For example, Bobick and Davis [1] accumulated foreground regions of a person as Motion History Images (MHI) to explicitly track shape changes. Tian *et al*. [11] employed Harris detector and local HOG descriptor on MHI to perform action recognition and detection. Similar to MHI, the proposed DMM also stacks foreground motion regions to record where and how actions are performed. However, there are main differences: 1) MHI only keeps most recent movements to capture the recency of motion, while DMM accumulates global activities through entire video sequences to represent the motion intensity; 2) our method stacks motion regions from front/side/top views, i.e. three orthogonal projections of depth maps, while only a single view is used in MHI. In the most recent work, local spatio-temporal features have been extensively used. As object recognition using sparse local features in 2D images, an action system first detects interest points [3, 5-6] and then computes descriptors based on the detected local spatio-temporal volumes. The local features are then combined (e.g. bag-of-words) to model different activities. The fundamental difference between those systems and our method is that they designed features based on 2D video sequences, instead of 3D depth maps that include supplementary information of body shape and movements.

With the release of RGBD sensors, research of action recognition based on depth information has been explored. Li *et al*. [7] proposed a Bag-of-3D-Points model for action recognition. They sampled a set of representative 3D points from depth maps to characterize the posture being performed in each frame. In order to select the representative 3D points, they first projected depth maps onto three orthogonal Cartesian planes and sampled 2D points at equal distance along contours of the three projections. The 3D points were then retrieved in depth maps according to the contour points. The experimental results showed that this method greatly outperformed the approach only using 2D silhouettes and was more robust to occlusion. However, in their experiments, the sampled 3D points of each frame generated a considerable amount of data which resulted in prohibitively expensive computations in clustering training videos of all classes. In contrast to their approach, our method is more compact and discriminative by computing HOG descriptors from DMM.

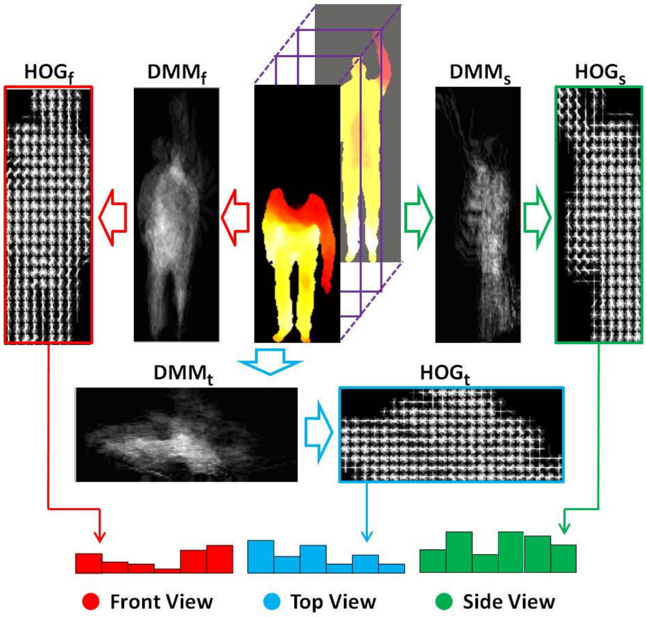

Figure 2. The framework of computing DMM-HOG. HOG descriptors extracted from depth motion map of each projection view are combined as DMM-HOG, which is used to represent the entire action video sequences.

3. COMPUTAION OF DMM-HOG

The framework to compute action representation of DMM-HOG is demonstrated in Fig. 2. We project depth frames onto three planes and compute associated motion energy, which are then stacked to obtain DMM. HOG descriptors are extracted from three depth motion maps and concatenated as the final action representation of DMM-HOG.

3.1 Depth Motion Maps (DMM)

In order to make use of the additional body shape and motion information from depth maps, each depth frame is projected onto three orthogonal Cartesian planes. We then set the region of interest of each projected map as the bounding box of foreground (i.e. non-zero) region, which is further normalized to a fixed size. This normalization is able to reduce intra-class variations, e.g. subject heights and motion extents, of different subjects when they perform the same action. So each 3D depth frame generates three 2D maps according to front, side, and top views, i.e. map_f, map_s, and map_t. As for each projected map, we obtain its motion energy by computing and thresholding the difference between consecutive maps. The binary map of motion energy indicates motion regions or where movement happens in each temporal interval. It provides a strong clue of the action category being performed. We then stack the motion energy through entire video sequences to generate the depth motion map DMM_v for each projection view:

$$DMM_v = \sum_{i=1}^{N-1} \left(\left| map_v^{i+1} - map_v^{i} \right| > \epsilon \right)$$

where $v \in \{f, s, t\}$ denotes the projection view; map_v^i is the projected map of the ith frame under projection view v; N is the number frames; $\left| map_v^{i+1} - map_v^{i} \right| > \epsilon$ is the binary map of motion energy; and ϵ is the threshold. We empirically set $\epsilon = 50$ in our experiments. As shown in Fig. 2, the DMM generated from an action video of *Pickup & Throw* demonstrate specific appearances and shapes, which characterize the accumulated motion distribution and intensity of this action. The DMM representation encodes the 4D information of body shape and motion in three projected planes, meanwhile significantly reduces considerable data of depth sequences to just three 2D maps.

3.2 DMM-HOG Descriptor

HOG is able to characterize the local appearance and shape on DMM rather well by the distribution of local intensity gradients. The basic idea is to compute gradient orientation histograms on a dense grid of uniformly spaced cells and perform local contrast normalization. In each cell, 4 different normalizations, i.e. L1-norm, L2-norm, L1-sqrt, and L2-Hys [2], are computed based on adjacent histograms. As for each depth motion map, we evenly sample 23×10 non-overlapping cells and 8 gradient orientation bins. So each DMM_v generates a descriptor HOG_v with the dimension of $4 \times 23 \times 10 \times 8 = 7360$. As shown in Fig. 2, we concatenate $[HOG_f, HOG_s, HOG_t]$ as the DMM-HOG descriptor which is the input to a linear SVM classifier to recognize human actions.

4. EXPERIMENTS AND DISCUSSIONS

The proposed method is evaluated on the MSR Action3D dataset [15]. We extensively compare our approach with the state-of-the-art methods under a variety of experimental settings. We further investigate how many frames are sufficient to recognize actions using DMM-HOG.

4.1 Experimental Setup

The MSR Action3D [15] is a public dataset with sequences of depth maps captured by a RGBD camera. It includes 20 action categories performed by 10 subjects facing to the camera during performance. Each action was performed 2 or 3 times by each subject. The depth maps are with the resolution of 320×240. The 20 action categories are chosen in the context of interactions with game consoles. As illustrated in Fig. 1, actions in this dataset reasonably capture a wide range of motions related to arms, legs, torso, and their combinations.

In order to facilitate a fair comparison, we follow the same experimental settings as [7] to split 20 categories into three subsets as listed in Table 1. As for each subset, there are three different tests, i.e. Test One (One), Test Two (Two), and Cross Subject Test (CrSub). In Test One, 1/3 of the subset is used as training the rest as testing; in Test Two, 2/3 of the subset is used as training and the rest as testing; in Cross Subject Test, half subjects are used as training and the rest ones used as testing.

Table 1. Action subsets and tests used in our experiments.

Action Set 1 (AS1)	Action Set 2 (AS2)	Action Set 3 (AS3)
Horizontal Wave	High Wave	High Throw
Hammer	Hand Catch	Forward Kick
Forward Punch	Draw X	Side Kick
High Throw	Draw Tick	Jogging
Hand Clap	Draw Circle	Tennis Swing
Bend	Hands Wave	Tennis Serve
Tennis Serve	Forward Kick	Golf Swing
Pickup Throw	Side Boxing	Pickup Throw

4.2 Evaluations of DMM-HOG

We first evaluate the effect of DMM normalization size to recognition performances. As discussed in Section 3.1, we normalize the three depth motion maps to a fixed size. Fig. 3 shows action recognition accuracies of DMM with different normalization sizes under a variety of test sets. The overall recognition rates of most test sets are similar across different DMM normalization sizes. As for AS1One and AS1Two, the size of 200×100 achieves the best results, while for AS2CrSub the size of 50×25 outperforms the others. Although lower resolutions are able to reduce computational cost in computing HOG, we extract HOG descriptors only from the three depth motion maps, instead of each video frame. So for each video, the difference of computation time between different sizes is small. The following experimental results are based on the size of 200×100. As shown in Fig. 3, while the performances in AS1CrSub are promising, the accuracy rates in AS2CrSub and AS3CrSub are relatively low. In Cross Subject Test, different subjects perform actions with great variations but the amount of subjects is limited, which results in considerable intra-class variations. Furthermore, some actions in AS2 are quite similar, e.g. *Draw X*, *Draw Tick*, and *Draw Circle*, which generates small inter-class variations. The performances on cross subject test might be improved by adding in more subjects.

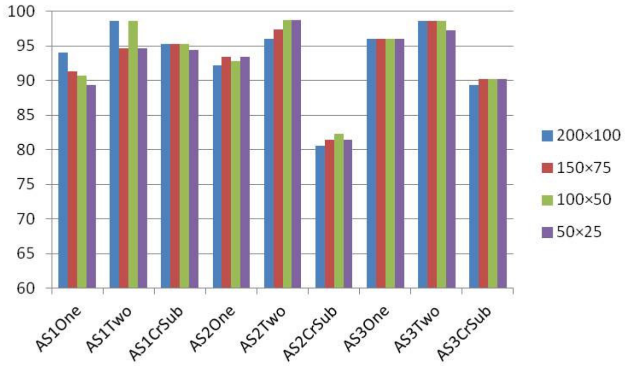

Figure 3. The recognition rates (%) of DMM with different normalization sizes under a variety of test sets.

4.3 How Many Frames Are Sufficient

Most existing systems [3, 5-7] recognize actions by operating on entire video sequences. We perform experiments to investigate how many frames are sufficient for action recognition with reasonably accurate results in our framework. The recognition rates using different amount of frames under a variety of test sets are demonstrated in Fig. 4. The sub-sequences are chosen from the first K frames of a given video. As shown in this figure, in most cases 30-35 frames are sufficient to achieve comparable results to the ones using entire sequences, with quite limited gains or even some loss as more frames are added in. As affect recognition in [4], the temporal segments of an action can be intuitively approximated by the status of neutral, onset, apex, and offset. The most discriminative information is within the status of apex and onset, which are probably covered by the first 30-35 frames of the MSR Action3D dataset. The sequences after apex contribute little or even incur more noise. This observation provides important guides to reduce latency of action recognition systems where decisions have to be made on line. The following results are based on the sub-sequence of first 35 frames.

4.4 Comparisons to the State-of-the-Art

We compare our DMM-HOG approach with the state-of-the-art method [7] on the MSR Action3D dataset [15] in Table 2. The recognition accuracies of Bag-of-3D-Points are obtained from paper [7]. The best results under different test sets are highlighted

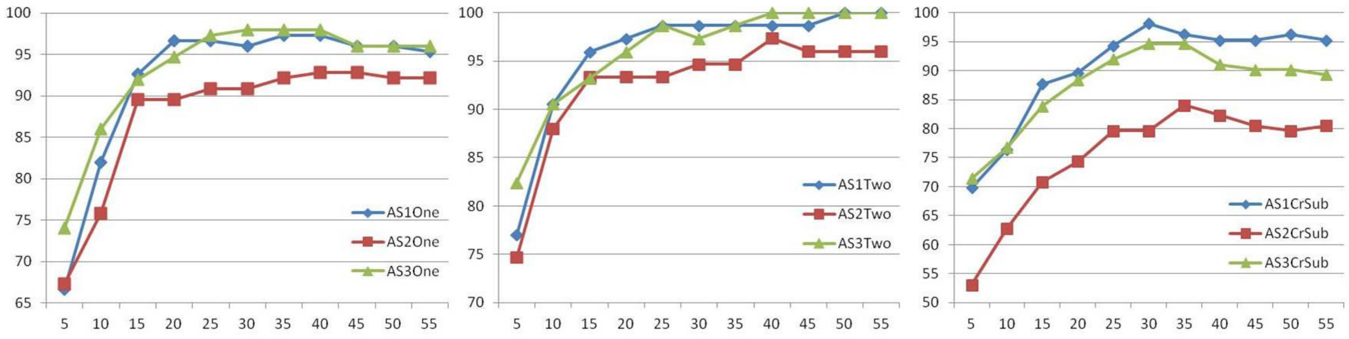

Figure 4. The recognition accuracies (%) using different number of frames in Test One (left), Test Two (middle), and Cross Subject Test (right). 30-35 frames are sufficient to enable action recognition in most test sets.

in bold. As shown in this table, our method consistently and considerably outperforms the Bag-of-3D-Points, especially for Cross Subject Test. The average recognition rates of our method in Test One, Test Two, and Cross Subject Test are 95.8%, 97.3%, and 91.7%, which improves the average accuracies of [7] by 4.2%, 3.1%, and 17.0%, respectively. The significant improvement of our method in Cross Subject Test is probably because the normalization process in computing depth motion maps helps to reduce variations of different subjects as well as the robust action representation of DMM-HOG. In addition to recognition accuracy, out approach is much more compact than the Bag-of-3D-Points model. Moreover, our method achieves the state-of-the-art results using a short sub-sequence (35 frames), while Bag-of-3D-Points relied on the entire video sequences.

Table 2. Recognition rates (%) of our method compared to the state-of-the-art approach on MSR Action3D dataset.

	Bag-of-3D-Points [7]	our method
AS1One	89.5	**97.3**
AS2One	89.0	**92.2**
AS3One	96.3	**98.0**
AS1Two	93.4	**98.7**
AS2Two	92.9	**94.7**
AS3Two	96.3	**98.7**
AS1CrSub	72.9	**96.2**
AS2CrSub	71.9	**84.1**
AS3CrSub	79.2	**94.6**

5. CONCLUSION

In this paper, we have proposed an effective action recognition method by using DMM-HOG descriptors. The compact and discriminative action representation is able to capture the global activities from front/side/top views. The experimental results on MSR Action3D dataset demonstrate that our approach significantly outperforms the existing state-of-the-art method. In addition, we observe that in our framework a short sub-sequence of 30-35 frames is sufficient to perform action recognition with reasonably accurate results. The future work will focus on combining body joints and depth maps to recognize actions, and incorporating more subjects to improve recognition in the cross subject test.

6. ACKNOWLEDGEMENT

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