Recognition of Human Actions from RGB-D Videos Using a Reject Option

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Abstract. In this paper we propose a method for recognizing human actions by using depth images acquired through a Kinect sensor. The depth images are represented through the combination of three sets of well-known features, respectively based on Hu moments, depth variations and the $\mathfrak{R}$ transform, an enhanced version of the Radon transform. A GMM classifier is adopted and finally a reject option is introduced in order to improve the overall reliability of the system. The proposed approach has been tested over two datasets, the Mivia and the MHAD, showing very promising results.

1 Introduction

The need for security in different applications fields, ranging from surveillance to patient monitoring systems, has led to a growing interest in those applications able to automatically interpret human behaviors. In this field, human action recognition is among the most challenging tasks.

According to [11], an action can be represented following two different approaches: local representation and global representation. Local representation is based on a bottom-up approach: the spatio-temporal interest points are extracted from the entire scene and local descriptors are then computed and combined into a final representation. For instance, a Microsoft Kinect sensor is used in [18] and [14]: the former proposed a novel 4D local spatio-temporal feature which combines both intensity and depth information; in the latter the features are based on human pose and motion, as well as on image and point-cloud information. Furthermore, the authors create a two-layer Maximum Entropy Markov strategy for modeling an activity as a set of sub-activities and exploit a dynamic programming approach for the inference. In [6] an unsupervised feature learning is proposed: the spatio-temporal features are learnt directly from unlabeled video data by means of an extension of the Independent Subspace Analysis algorithm. The main success of all these methods based on local features is that any kind of pre-processing methods, such as motion segmentation and tracking, can be avoided. Furthermore, such methods are invariant to changes in viewpoint, person appearance and partial occlusions. The main lack, however, lies in their computational burden: these techniques are usually very slow, and their applicability to real-time systems is not really feasible. For instance, in [6] the computation needs 0.44 seconds for each frame, 0.10 seconds only if the implementation is optimized for a GPU.

On the contrary, in global representation based approaches the visual observation focuses on a Region of Interest (ROI): the person is located in the scene by applying background subtraction or tracking techniques; the descriptors in this case are usually derived from silhouettes, edges or optical flow. For instance, in [2] and [17] a Radon transform and an extended version, the $\mathfrak{R}$ transform, have been respectively adopted. In particular, the $\mathfrak{R}$ transform is invariant to scale and translation and, as experimentally demonstrated in [17], outperforms methods using silhouette-based moment descriptors (like, for instance, Invariant Moments, Zernike Moments, Pseudo-Zernike Moments and Wavelet Moments) without increasing the computational cost. In [9] each action is represented by its 3D volume (two spatial and one temporal dimensions); the characterization of this volume is performed by geometrical moments based on Hu moments [1]. In [8] RGB-D images are considered. Such approaches significantly improve the extraction of the silhouette, being insensitive to the typical problems of the detection phase (like, for instance, illuminance conditions changes or camouflage). However, the main problem in the approaches based on global representations lies in the fact that such techniques are sensible to noise, partial occlusions and variations in viewpoint. In order to overcome these limitations, global representations are often enriched by a grid-based approach: the ROI is partitioned into cells in order to also obtain local information about the part of the objects in the scene.

The proposed method belongs to the last category: RGB-D images acquired by a Kinect are processed in order to extract the moving object silhouette. A first original aspect of the method is the use of a combination of three well-known different sets of features, respectively based on the $\mathfrak{R}$ transform, depth variations and Hu moments. The first set is good at capturing properties related to the alignment of subregions of the image, while the second set describes in a more global way the overall distribution of the pixels; thus they are quite complementary in their nature, and their combination improves the discriminant ability with respect to each set taken separately. Also note that both sets are based on integral criteria, and so are quite robust with respect to noise.

The classification is performed by means of a Gaussian Mixture Model (GMM) classifier. A second major novelty of the method is the addition, after the classifier, of a module that estimates the reliability of the single classification response. This module is able to reject (i.e. refrain from recognizing an action) when observing a sample whose reliability is low. In this way the system avoids issuing erroneous action reports for ambiguous or unstable situations, such as during the transition between two different actions, thus improving the classification performance.

2 The Proposed Method

This section will detail the proposed method: two main phases can be identified, as shown in Figure 1: a *low-level* phase (colored in orange in the figure), aimed at extracting features starting from the analysis of raw data, and a *high-level* phase (in blue in the figure), devoted to identify the actions of the object of interest, by analyzing the extracted features. More details about each module will be provided in the following.

Fig. 1. Overview of the proposed method

2.1 Low-Level Phase

This phase includes acquisition of the images, their representation, and feature extraction. Each of these steps is described in the following.

Acquisition: The raw images are acquired using a Kinect, an affordable (under \$150) input device produced by Microsoft, that provides both a RGB image and a depth image obtained by means of an infrared image sensor combined with a structured infrared light source.

Representation: The depth image D is processed to obtain three different representations, the *Motion History Image* (MHI), the *Average Depth Image* (ADI) and the *Depth Difference Image* (DDI); these three representations will be used as the basis for feature extraction. The *Motion History Image* MHI [4] is used to capture into a single and static image the sequence of motions. The value of MHI at time t and position (x, y) is updated as follows:

$$MHI(x, y, t) = 255 \quad (1)$$

if point (x, y) passed from background to foreground at time t , and

$$MHI(x, y, t) = \max\{M(x, y, t - 1) - \tau, 0\} \quad (2)$$

otherwise; τ is a constant.

Given an observation window of N temporally adjacent images, the *Average Depth Image* $ADI(x, y, t)$ [8] is the average depth at position (x, y) over the images at times $t - N + 1, \dots, t$.

Finally, the *Depth Difference Image* DDI [8] is used to evaluate the motions changes in the depth dimension:

$$DDI(x, y, t) = D_{\max}(x, y, t) - D_{\min}(x, y, t), \quad (3)$$

where $D_{\max}(x, y, t)$ and $D_{\min}(x, y, t)$ are respectively the maximum and minimum depth for position (x, y) over the images at times $t - N + 1, \dots, t$.

It is worth pointing out that N in our experiments is set to one second, corresponding to 25 frames. Furthermore, in [8] it has been experimental evaluated that the optimal value of τ is $(256/N) - 1$.

Features Extraction: Once obtained the derived images, three different kinds of features have been extracted. In particular, Hu moments [1] have been chosen to represent the MHI and ADI, while the DDI is represented through two different kinds of features: the $\mathfrak{R}$ transform [15] and the Min-Max Depth Variations [8]. The former is an extended Radon transform; its main advantages lie in its low computational complexity and its geometric invariance: in particular, such a descriptor is robust with respect to the errors of the detection phase, such as disjoint silhouettes and holes in the shape. The latter is obtained by hierarchical partitioning the box containing the silhouette into cells of equal size and by computing the maximum and the minimum values in each cell (see Figure 2).

It is worth pointing out that the features extraction step results in a vector composed by 303 features: 14 for the Hu moments, 181 representing the $\mathfrak{R}$ transform and 108 encoding the Min-Max Depth Variations over the grid.

Fig. 2. Min Max Depth Variations Features extracted with hierarchical grids

2.2 High-Level Phase

The high-level phase is composed by feature reduction, classification and reject module, described below.

Feature reduction: In order to improve the performance of the system, both in terms of overall accuracy and computational cost, a Principal Component Analysis (PCA) and a Linear Discriminant Analysis (LDA) are used for reducing the dimensionality of the feature vectors. This combination has been often used for face recognition applications (the reader can refer, for instance, to [7]), showing a significant improvement in the overall accuracy of the methods.

Classification: Once obtained the reduced features vector, a Gaussian Mixture Model (GMM) classifier is used for the final step. During the training step, the distribution of each class is estimated by maximizing the likelihood. During the classification phase, the likelihood for each class is computed; before assigning the observation to the class for which the likelihood is maximum, the system computes the estimation of the reliability of the obtained results ψ . If ψ is below a given threshold σ^* , then the sample will be rejected. According to the method proposed in [5], ψ can be computed as the combination of two different terms, ψ_a and ψ_b , that account for the typical situations that usually make low the reliability of a classifier: (a) the sample significantly differs from those present in the training set; (b) the point representing the sample in

the features space lies at the boundary between two classes. In particular, for the GMM classifier ψ_a can be computed as

$$\psi_a = O_{win}, \quad (4)$$

being O_{win} the maximum likelihood computed. Similarly, ψ_b can be computed as

$$\psi_b = O_{win} - O_{2win} \quad (5)$$

where O_{2win} is the likelihood of the second best class. In conclusion, for the GMM classifier,

$$\psi = \min\{O_{win}, O_{win} - O_{2win}\} = \psi_b. \quad (6)$$

Reject Module: This step compares the reliability indicator ψ with a threshold σ , and rejects the sample if it is below the threshold. The reject option has been successfully used in other application fields, ranging from audio-surveillance [3] to biomedical analysis [13]. At our knowledge, it is used for the first time in this paper for actions recognition purposes. The method for choosing an optimal threshold σ^* is described in [5]. The main idea is that σ^* can be computed by maximizing a function P , which measures the classification effectiveness in the considered application domain, in terms of recognition rate R_c , error rate R_e and reject rate R_r . Assuming a linear dependence for P on R_c , R_e and R_r , P can be computed as follows:

$$P = C_c \cdot (R_c - R_c^0) - C_e \cdot (R_e - R_e^0) - C_r \cdot R_r, \quad (7)$$

being R_c^0 and R_e^0 respectively the recognition rate and the error rate at 0-reject. Furthermore, C_e , C_r and C_c respectively represent the cost of each error, of each rejection and the gain of each correct classification. Of course, such costs strongly depend on the particular application domain.

It should be clear that R_c , R_e and R_r depend on σ . It means that also P is a function of the reject threshold. Since this function is not available in analytic form, the optimal threshold σ^* has to be experimentally evaluated by means an exhaustive search among the tabulated values of $P(\sigma)$.

3 Experimental Results

In the last years, a lot of datasets for action recognition have been proposed. However, they usually have two limitations with respect to the needs of our experimentation: first, the RGB-D images are not available [12] or, if available, the background is not included in the dataset [16]. This issue is justified by the fact that a lot of methods are not based on background subtraction strategies, since they directly extract the objects skeletons from the images. The second limitation depends on the typology of the extracted data: as a matter of fact, we are mainly interested in actions with a high semantic level (eating, drinking etc.). Most of the available datasets, instead, mainly focus on actions with low semantic level, like running, sitting down, standing up and so on. For the above mentioned reasons, we built our own dataset, from now on denoted as the Mivia Dataset;

however we also used an existing dataset, for making our results easier to compare with other. Thus, the used datasets were:

Mivia Dataset: it has been acquired in the Mivia lab and it is available at the following link: <http://mivia.unisa.it/datasets/video-analysis-datasets/mivia-action-dataset/>. It is composed by 7 high-level actions performed by 14 subjects (7 males and 7 females). All the subjects performed 5 repetitions of each action, so resulting in about 500 repetitions; the approximated length of each action is reported in Table 1.

Berkeley Multimodal Human Action Detection (MHAD) [10]: it contains 11 low-level actions performed by 7 male and 5 female subjects. All the subjects performed 5 repetitions of each action, yielding about 660 action sequences which correspond to about 82 minutes of total recording time.

Table 1 summarizes the actions recorded in each dataset, while Figure 3 shows some examples.

Table 1. Description of the Berkeley MHAD (a) and of the Mivia (b) Datasets

ID	Action	Length per Recording
A1	Bending - hands up all the way down	12 secs
A2	Clapping hands	5 secs
A3	Jumping in place	5 secs
A4	Jumping jacks	7 secs
A5	Punching (boxing)	10 secs
A6	Sit down	2 secs
A7	Sit down then stand up	15 secs
A8	Stand up	2 secs
A9	Throwing a ball	3 secs
A10	Waving - one hand (right)	7 secs
A11	Waving - two hands	7 secs

(a)

ID	Action	Length per Recording
B1	Opening a jar	2 sec
B2	Drinking	3 secs
B3	Sleeping	3 secs
B4	Random Movements	11 secs
B5	Stopping	7 secs
B6	Interacting with a table	3 secs
B7	Sitting	3 secs

(b)

For each dataset, two different experimentations has been conducted: in the first case, we did include the person to be tested in the training set; namely, one of the repetitions of each action performed by the person being tested was included in the training set, together with all the repetitions by all the other persons; the test has been repeated for all the persons in the database, and the average performance has been reported. This case represents the situation in which the person whose actions have to be recognized is known to the system, a situation that occurs in many applications (e.g. home monitoring of an elderly person). In the second case, the person to be tested is not included in the training set, which is formed by the actions of all the other persons. This case models the situation in which the actions of unknown persons have to be recognized, that occurs in applications like surveillance of public places.

The results, in terms of true positive rate, for the different sets of features (in particular $\mathfrak{R}$ features, used in [2], depth-based features (Hu Moments and Min-Max Depth Variation), used in [8], and their combination, first introduced in this paper) are shown in Tables 2 for the Mivia (a)(b) and the MHAD dataset (c)(d) respectively.

Fig. 3. Some examples of the Berkeley MHAD Dataset (A2 (a), A3 (b), A4 (c)) and of the Local Dataset (B1 (e), B2 (f), B4 (g))

On the Mivia dataset, the absolute performance for all the methods is quite high for the case of the test person included in the training set and (as expected) slightly worse for the case of the test person excluded. On the other hand, the performance on MHAD is lower; it is worth pointing out that the MHAD is a very challenging dataset: actions like, for instance, *Sit down* and *Sit down then stand up* are very similar to each other (the first two seconds are exactly the same). However, the interesting point is that in both the test cases, and for both the datasets, the proposed method results in a measurable improvement of the classification accuracy; the improvement is usually between 2% and 3%, but for some actions it is quite larger (e.g. for action A5 of the MHAD database, in the unknown person scenario, the accuracy improvement is 18%).

Finally, we evaluated the impact of the reject option on the classifier performance, by comparing the error rates of a zero-reject classifier with the error and reject rates of a classifier using the optimal reject threshold previously defined (for this experiment we set the costs as $C_r = 2$, $C_e = 5$ and $C_c = 1$).

Table 3 shows the obtained results. As it can be seen, for the Mivia Dataset the improvements were negligible. However, on the more difficult MHAD Dataset the reject option is able on the average to reduce the error rate by an additional 2.3%, thus confirming its usefulness.

Finally, as for the computational cost, we verified that the proposed method is able to run at 10 fps on a MacBook Pro equipped with Intel Core 2 Duo running at 2.4 GHz, so confirming its applicability in real frameworks.

Table 2. Recognition rates over the Mivia dataset (a)(b) and over the Berkeley MHAD dataset (c)(d) with a different feature set ($\mathfrak{R}$ Features, Depth Features and the combination of both), with and without the person under test in the training set

The test person is in the training set			
	$\mathfrak{R}$ Features	Depth Features	Proposed Method
B1	47.453	91.491	93.340
B2	39.068	93.825	94.660
B3	97.913	99.986	99.987
B4	85.858	98.809	98.709
B5	89.225	98.791	99.222
B6	35.400	98.475	98.950
B7	65.596	98.756	98.808

(a)

The test person is NOT in the training set			
	$\mathfrak{R}$ Features	Depth Features	Proposed Method
B1	33.574	82.604	83.677
B2	23.356	77.794	73.967
B3	80.297	97.694	99.893
B4	85.234	98.023	97.526
B5	85.532	91.533	88.287
B6	23.442	96.360	98.033
B7	43.529	93.090	94.753

(b)

The test person is in the training set			
	$\mathfrak{R}$ Features	Depth Features	Proposed Method
A1	56.462	83.829	86.483
A2	82.999	94.405	95.195
A3	43.124	72.556	83.223
A4	84.020	88.273	91.518
A5	46.405	87.504	88.999
A6	24.020	66.612	75.456
A7	34.110	81.843	80.327
A8	38.912	84.854	81.829
A9	24.985	77.894	81.038
A10	80.270	95.823	96.726
A11	71.628	83.208	89.233

(c)

The test person is NOT in the training set			
	$\mathfrak{R}$ Features	Depth Features	Proposed Method
A1	49.282	69.942	74.974
A2	44.101	54.580	58.969
A3	22.971	41.651	47.450
A4	77.814	69.151	67.886
A5	33.051	52.447	70.201
A6	12.540	32.554	35.468
A7	21.803	66.086	59.943
A8	19.130	47.467	48.957
A9	6.407	58.167	57.384
A10	44.783	78.271	79.512
A11	56.996	62.380	64.903

(d)

Table 3. Performance of the system over the Mivia and the MHAD datasets, in terms of Error Rate (with and without reject) and Reject Rate

Mivia Dataset			
Class	Error Rate without reject	Error Rate with reject	Reject rate
B1	6.66	5.53	2.49
B2	5.34	4.35	1.83
B3	0.01	0.01	0.01
B4	1.29	1.20	0.14
B5	0.78	0.52	0.63
B6	1.05	0.89	0.17
B7	1.19	1.16	0.04
Total	2.33	1.95	0.76

MHAD Dataset			
Class	Error Rate without reject	Error Rate with reject	Reject rate
A1	13.52	11.39	2.99
A2	4.80	3.66	1.40
A3	16.78	13.22	5.32
A4	8.48	7.36	1.64
A5	11.00	9.99	1.47
A6	24.54	21.94	5.06
A7	19.67	17.82	3.41
A8	18.17	15.11	4.84
A9	18.96	16.22	4.35
A10	3.27	2.58	1.16
A11	10.77	8.56	3.01
Total	15.25	12.90	3.59

4 Conclusions

In this paper we proposed a framework for recognizing human activities by analyzing depth images extracted from a Kinect sensor. The experimental results show that the combination of the three sets of features, respectively based on Hu moments, depth variations and $\mathcal{H}$ transform, consistently improved the performance of the system. The overall reliability is further enhanced by introducing a reject option, which has been exploited for the first time in this paper in the field of action recognition.

Acknowledgment. This research has been partially supported by A.I.Tech s.r.l. (a spin-off company of the University of Salerno, www.aitech-solutions.eu).

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