Human activity recognition in the semantic simplex of elementary actions

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Abstract

This paper presents an original approach for recognizing human activities in video sequences. A human activity is seen as a temporal sequence of elementary action probabilities. Actions are first generically learned using a robust action recognition method based on optical flow estimation and a cross-dataset training process. Activities are then projected as trajectories on the semantic simplex in order to be characterized and discriminated. A new trajectory attribute based on the total curvature Fourier descriptor is introduced. This attribute takes into account the induced geometry of the simplex manifold. Experiments on labelled datasets of human activities prove the efficiency of the proposed method for discriminating complex actions.

1 Introduction

1.1 Context

Analyzing and recognizing human actions in videos has received considerable attention for many years in the computer vision community. Works on this topic are motivated by several potential applications (video monitoring, automatic video indexing, crowd analysis, human-machine interaction, etc). The wide variability of human actions makes it difficult to design generic methods (datasets of sport activities, daily activities, different contexts of action, etc). Two kinds of approaches for tackling human action recognition can be outlined. The first approaches tend to consider an action as a set of low-level features extracted from a group of frames (for instance histograms of spatio-temporal points). This constitutes what we call an elementary action, such as *walking* or *jumping*. The second approaches represent an order set of semantic attributes, and is called an activity. This is the framework of the proposed method: human activities are complex actions which are made of an ordered set of different elementary actions. For instance, *high jumping* can be decomposed into different elementary actions over time: *walking*, *running* and *jumping*.

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1.2 Human activities: a brief state of the art

Different approaches have been developed to address human action recognition. Most of them are based on discriminative supervised models. The goal is to discriminate different actions performed by one or several subjects using algorithmic methods trained on already labeled video sequences. To detect and describe relevant features in videos, several discriminative approaches are using a temporal extension of 2D interest point detector. Laptev *et al.* [10] were the first to propose the Spatio-Temporal Interest Point detector (STIP) which is a temporal extension of the Harris-Laplace 2D detector [7]. It is efficient on constrained video datasets such as KTH Dataset [17]. Dollar *et al.* [9] provide the cuboïd detector and descriptor adapted for periodic movements in video, or for facial expression recognition. In [24] Willem *et al.* extend the 2D detector SURF [1] in the temporal domain to detect saliency using the determinant of 3D Hessian matrix. Wang *et al.* in [22] are adding temporal information by estimating point trajectories, using a dense sampling strategy at regular time intervals. Trajectories allow to better capture temporal information of motion of interest. Raptis *et al.* [14] also use gradient and optical flow information to encode salient point trajectories. Vrigkas *et al.* [21] represent actions using a Gaussian mixture model by clustering motion curves computed from optical flow estimation.

Other studies are focused on generative probabilistic models for human activities or complex actions. Unlike elementary actions, activities require a much longer temporal observation. They commonly represent human daily behavior, sport actions, human interactions and most of them can be decomposed into different short elementary actions. Activities have a higher semantic level compared to elementary actions. Most generative models are based on Latent Dirichlet Allocation algorithm (LDA) [3] originating from document retrieval. This algorithm brings out underlying document topics. This framework allows the characterization of any type of data as a proportion of topics which compose it. A complex action is then defined as a collection of topics. A SVM classifier is generally applied on the collection of topics to discriminate between activities. Niebles *et al.* explore topic generation for human activities in [13] as a non-supervised action learning using a Bag of visual Words. The BoW is built using features such as the cuboïd descriptor [9]. Tavernard *et al.* [18] represent videos as sequential occurrences of visual words obtained from STIP detector. Hierarchical LDA is thereafter used to take into account the chronological structure of visual words. Wang *et al.* [23] have introduced semi-supervised LDA to constrain correspondance between generated topics and already known action classes. Nevertheless, generative models such as LDA fail to match already known actions occurring in videos with topics generated in a non-supervised way. Moreover, it is difficult to semantically analyze discovered topics. In fact, in the original version of the LDA, there is no possibility to bring an *a priori* information on already known actions and to ensure a correspondance between generated topics and present actions in the video. Methods using *a priori* information are less efficient than discriminative methods on classification of elementary actions. Moreover, most of them are using global descriptors which have shown their limitation for action recognition.

In this paper, we present an original approach for human activities recognition in videos. It relies on a semantic representation of videos rather than a Bag of visual features approach, allowing better generalization. We characterize activities as temporal sequences of elementary actions by estimating their probabilities over time. Elementary actions are not discovered as in generative probabilistic models but learned via a robust action recognition method based on a discriminative model. These activities are then projected as trajectories on the semantic simplex of elementary actions. These action trajectories are processed and characterized

using a metric taking into account the geometry of the simplex manifold.

2 Recognition of elementary actions

2.1 A method based on optical flow estimation

To recognize elementary actions, we use an approach developed in our previous works [2] where video sequences are characterized by critical points of the optical flow and by their temporal trajectories. These features are computed at different spatio-temporal scales, using a dyadic subdivision of the sequence. Features are extracted and correspond to different frequency scales (fast and slow movements, respectively at high and small scales - illustrated on Figure 1).

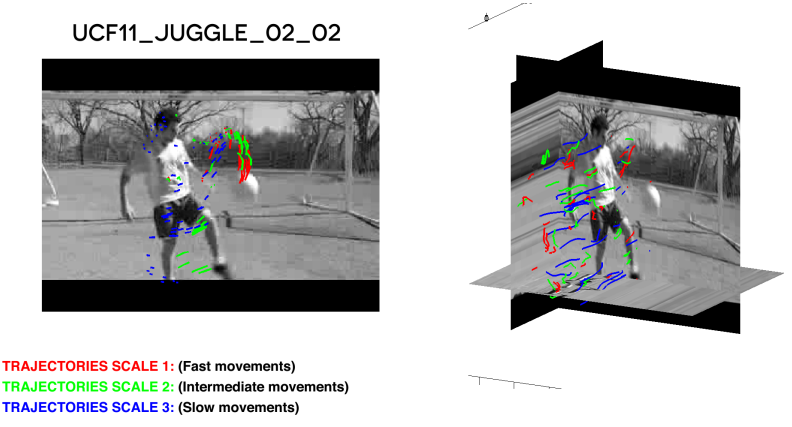


Figure 1: Example of movements captured at different frequency scales. Red trajectories correspond to high frequency movements (fast). Blue trajectories correspond to low frequency movements (slow). Green trajectories correspond to an intermediate frequency scale.

Critical points are locally described by spatial gradients and motion orientation descriptors [11] (namely the HOG and HOF descriptors). Multi-scale trajectories are thereafter frequentially described using Fourier transform coefficients, which ensures robust invariance to geometric transformations. These three characteristics (shape, orientation of movement and frequency) have proven to be complementary and relevant for elementary actions recognition.

2.2 Cross-dataset learning

In order to characterize an activity as an ordered sequence of elementary actions, a robust and generic representation of the elementary action has to be extracted. Here, we have selected the `KTH dataset` [17], the `Weizmann dataset` [6], the `UCF-11 dataset` [12] and the `UCF-50 dataset` [15] to represent different aspects of human actions. `KTH` and `Weizmann` are datasets containing videos with acquisition constraints. Subjects in those videos are performing elementary actions (*jumping*, *waving*, *walking*, *running*, *boxing*, *etc*) in a canonical way. In `UCF-11` and `UCF-50`, elementary actions are captured in real situations and contexts. These latter bring visual variabilities and movements which are not specific to

the action of interest. Generic and constrained datasets are complementary for representing elementary actions at different frequencies of movement. We combine videos from both types of datasets to perform a cross-dataset learning in order to provide a robust and generic description of elementary actions.

Four elementary actions from common activities are thereafter considered: `Jump`, `Run`, `Walk`, and `Handwave`. In the cross-dataset learning process, we have made the choice of using 1/3 of generic videos (`UCF-11`, `UCF-50`) and 2/3 of constrained videos (`KTH` and `Weizmann` datasets). Table 1 shows results obtained after a Leave-One-Out cross-validation test when the classifier is trained on this mixture dataset. The global recognition rate is 96.87%. Confusion appears between semantically related classes. We have used an Adaboost late fusion scheme [8] to combine each feature descriptor.

Actions	*jump*	*walk*	*run*	*wave*
jump	90.62	0	9.37	0
walk	0	100	0	0
run	0	3.12	96.87	0
wave	0	0	0	100

Table 1: Confusion matrix of the mixture dataset learning

The recognition rate per descriptor and Adaboost weight are shown in Table 2. The HOG descriptor computed weight is the lowest among these three descriptors, as expected with a hybrid dataset. Efros *et al.* have indeed shown that most of common datasets have an important visual bias [19].

Descriptors	FCD	HOF	HOG
Rec. rate	94.53%	95.31%	53.12%
Adaboost weight	2.91	1.82	0.42

Table 2: Recognition per descriptor and weight obtained by Adaboost late fusion.

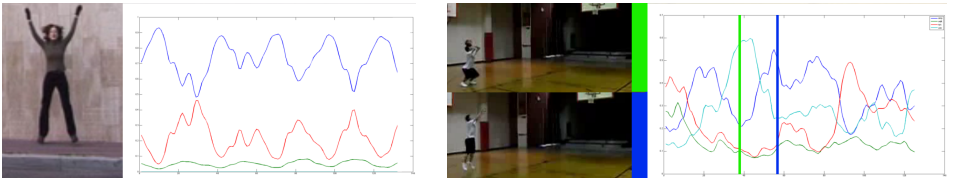
Mixing videos from different datasets increases the visual variability in the scene and weaken gradient information whereas information related to motion remains quite stable.

3 Representation of complex actions by a sequence of elementary actions

3.1 Probability of elementary actions

In our method, a complex action is viewed as a sequence of elementary action proportions. To evaluate the temporal evolution of these proportions, the decision boundaries of the classifier are transformed into probabilities [5].

Elementary action probabilities are then computed over time using a sliding window along the video sequence. The goal is to characterize a frame t by its elementary action probabilities in a $[t-N;t+N]$ window. It is assumed that elementary actions are commonly performed on a short time period. Schindler *et al.* [16] have indeed shown that few images are needed to achieve good recognition rates on elementary action datasets. Figure 2 illustrates the decomposition on a video from the `Weizmann dataset`.



(a) (b)

Figure 2: (a) `Jack` and (b) `Basket-ball` actions with their representation as a sequence of elementary action probabilities.

The `Jack` action (Fig. 2.a) is composed of `Jump` and `Handwave` elementary actions. The graph represents the evolution of elementary action probabilities over time. Red curve is for `Handwave` action, blue curve for `Jump` action. The periodicity and alternation between the two elementary actions is well noticeable on the graph. The other figure represents a `Basket-ball` action (Fig. 2.b), where the green bar indicates the "handwaving" instant of the shoot, which corresponds to a high proportion of the `Handwave` elementary action. The blue bar emphasizes the "jump" instant of the shoot, where `Jump` elementary action probability is high. These examples illustrate the ability of the action recognition method to provide a meaningful representation of generic actions using a mixture dataset.

3.2 Characterizing the absence of action

When elementary action probabilities are estimated, values depend on the most relevant actions among those that have been learned. When there is no movement in the sequence, it is necessary to adapt the classifier. To do so, the amount of potential movements present in the sliding window is estimated using the optical flow. Each frame of the sequence is subdivided in vertical and horizontal blocks and the mean power of the optical flow is computed. Finally, each frame t of the sequence is characterized by a coefficient $coef_{standing}(t) \in [0,1]$, proportional to the optical flow mean power and reflecting the degree of motion occurring in this frame. Probabilities estimated from the classifier are then normalized. An artificially generated action class is introduced, named the "`Standing` class". This class allows to inject in the classifier the presence or absence of movement in the sequence at time t.

The new *a posteriori* probability vector is then:

$$Prob_{estimates}(t) = [(1 - coef_{standing}(t))(\lambda_1(t), ..., \lambda_k(t), ..., \lambda_L(t)),\ coef_{standing}(t)]$$

with $\lambda_k(t)$ the probability of the elementary action at time t.

Figure 3 shows an example of improvement obtained using the `Standing` class (a related video is also available online in the supplementary materials). When no action is present in the sequence, probabilities are close to 0, except for the new standing class. The characterization of the absence of movement provides a richer description and a more relevant representation of the elementary actions over time.

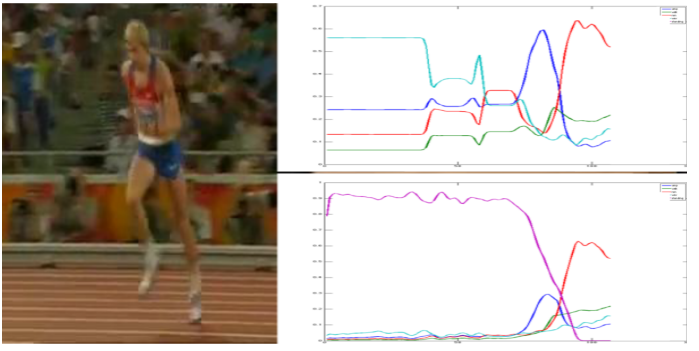


Figure 3: When a subject is standing before starting to run, the classifier gives chaotic results because of the absence of movement (top right figure). On the bottom right figure, the use of the `Standing` class (magenta curve) provides a better representation of the elementary actions occurring in the sequence.

4 Action semantic trajectories

4.1 Trajectory in the semantic space

Once a frame is characterized by its elementary action probabilities, its feature vector lies in a simplex $\mathcal{P}_L$ defined such as:

$\mathcal{P}_L = \{\pi \in R^{L+1} | \sum_{i=1}^{L+1} \pi_i = 1, \pi > 0\}$, $\mathcal{P}_L$ being a submanifold of R^{L+1}.

Figure 4 shows the global scheme for projecting activities in $\mathcal{P}_L$.

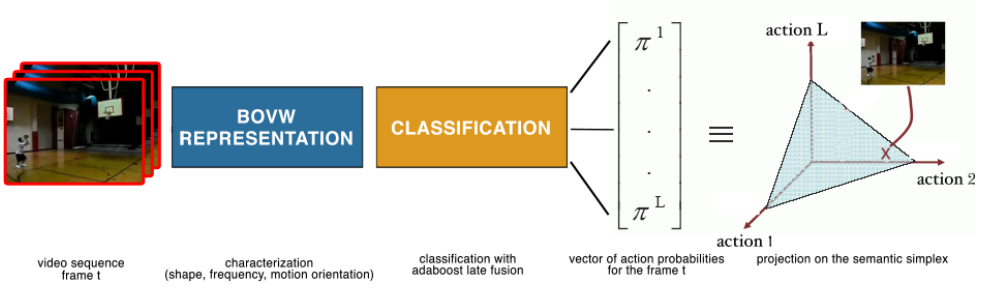


Figure 4: Global scheme for characterizing activities in the semantic simplex.

Activities are then represented as trajectories on the semantic simplex $\mathcal{P}_L$. The transformation:

$$F : \begin{cases} \mathcal{P}_L \to \mathcal{S}_L^+ \\ \pi = (\pi_1, ..., \pi_{L+1}) \to \theta = (2\sqrt{\pi_1}, ..., 2\sqrt{\pi_{L+1}}) \end{cases}$$

with:

$S_L^+ = \{\theta \in R^{L+1} | \sum_{i=1}^{L+1} \theta_i^2 = 2, \theta > 0\}$,

is a diffeomorphism of P_L into S_L^+. The L-simplex P_L is endowed with the Fisher information metric and the positive L-hypersphere $\mathcal{S}_L^+$ is endowed with the standard Euclidean metric on its surface [9].

Since F is an isometry, it emplies that geodesic distances in P_L can be computed as shortest curves on $\mathcal{S}_L^+$.
The geodesic distance between two points (π_{k1}, π_{k2}) of P_L is the great circle arc linking $(F(\pi_{k1}), F(\pi_{k2}))$ on S_L^+ such as:
$d_{\mathcal{S}_L^+}(F(\pi_{k1}), F(\pi_{k2})) = d_{\mathcal{S}_L^+}(\theta_{k1}, \theta_{k2}) = 2\cos^{-1}(\theta_{k1}\theta_{k2}^\top/4)$

4.2 Characterization of semantic trajectories through total curvature Fourier descriptor

Trajectories are characterized by their shapes on the manifold. By using the diffeomorphism F, trajectories lie on the hypersphere $\mathcal{S}_L^+$, and cartesian coordinates in R^{L+1}, are converted into spherical coordinates. They are defined by one radial coordinate r (in our case $r = 2$) and L angular coordinates $\phi_1, \phi_2, ..., \phi_L \in [0, 2\pi]$. The goal is to describe in the frequency domain the angular evolution over time of the shape on the half-positive hypersphere.
Fourier coefficients enable to obtain a robust shape descriptor. In the frequency domain, most of the shape information are included in the first lowest frequencies. One obtains a robust and global representation of trajectories by discarding high frequencies which correspond to less relevant information or noise. Considering only angular variations of the spherical coordinates ensures that any processing in the frequency domain will keep the resulting trajectory on S_L^+ (thus the sum of associated probabilities equals to 1).

Activity trajectories are open shapes in S_L^+. Reconstruction of shapes from low-frequency Fourier coefficients does not necessarily coincide with the end-points of the original shape. When removing high frequencies, it has a tendency to become a closed shape and to oscillate near end-points. To avoid this problem, the method of [20] for open curves is adapted. It corresponds to the Fourier transform performed on a cumulative angular curvature function. It preserves end-point positions of the original shape when it is reconstructed from only low frequencies of its Fourier descriptor (see Figure 5).

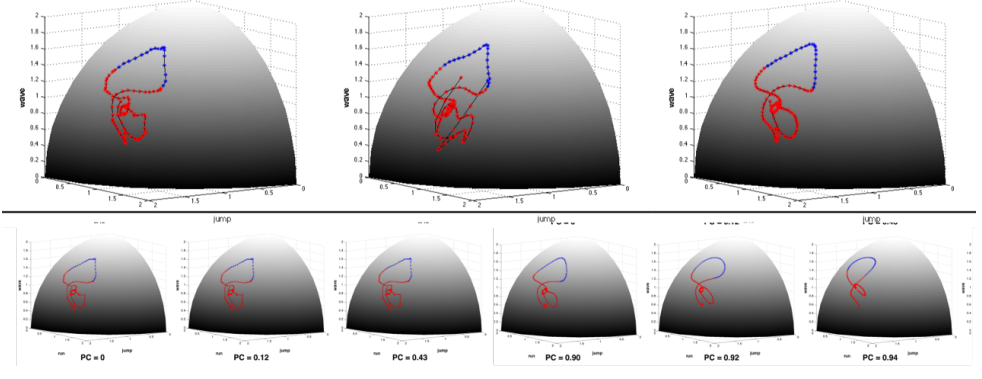


Figure 5: Top row: trajectory smoothing on $\mathcal{S}_L^+$. Left : original trajectory. Center: simplified reconstructed trajectory using standard Fourier descriptor. Right: simplified reconstructed trajectory using total curvature Fourier descriptor. Start-point and end-points keep the same position when using the total curvature function. Bottom row shows the reconstructed trajectory using a decreasing number of Fourier coefficients.

To characterize these trajectories, we concatenate the Fourier transform coefficients of the cumulative angular curvature of each trajectory angular coordinates. Because of the

geometry of the hypersphere, the resulting descriptor is not invariant to translations, scales and rotations: such invariance would not be here a desirable property. In fact, the position on the simplex depends on the actions performed during the activity. Two different activities which have trajectories with the same shape but do not share necessarily the same elementary actions. They will be on two different positions on S_L^+ (see Figure 6).

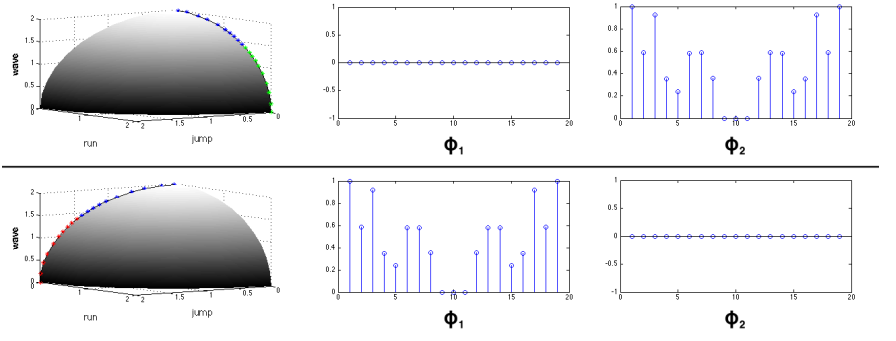


Figure 6: Trajectories having the same shape but different positions in the simplex. First trajectory (top row) goes from `Wave` action to `Run` action. Second trajectory (bottom row) goes from `Wave` action to `Jump` action. Because of the concatenation of angular coordinates ϕ, the two resulting descriptors are different.

5 Experiments

In order to test the discriminative performance of the proposed method, three complex actions from `UCF11`, `UCF50` datasets and `Olympic Sport` dataset are considered: `High-Jump`, `Basket-ball` and `Base-ball`. Figure 7 shows some trajectories for each activity class.

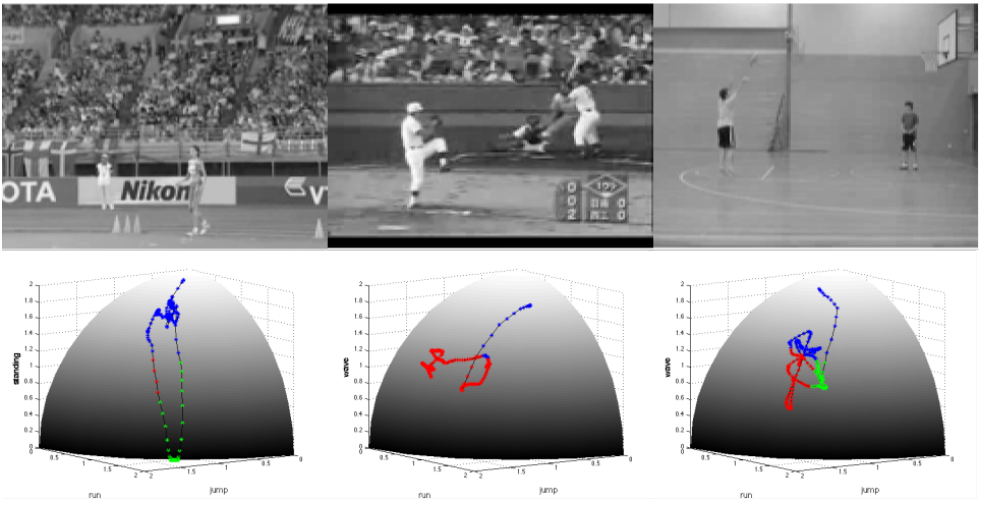
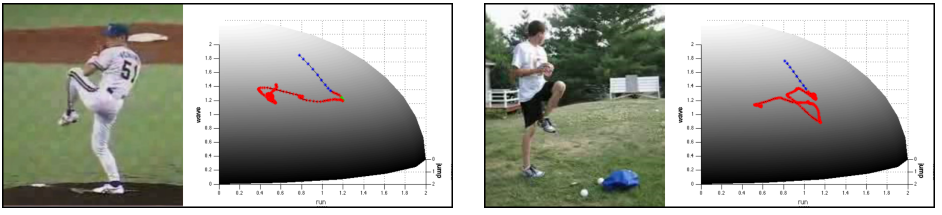


Figure 7: Examples of activity trajectories: `High-Jump` activity, `Base-ball` activity, and `Basket-ball` activity.

Activities in these datasets are performed with different points of view, speed and some visual variations (see Figure 8).



(a) (b)

Figure 8: Example of two `Base-ball` video sequences with different points of view sharing globally the same shape on the manifold.

Four elementary actions are used `Wave`, `Jump`, `Run` and `Walk` (setting $L = 5$ for taking into account the `Standing` class). We set the temporal window size to $N = 6$, and 10 videos for each class are considered.
The first step consists in up-sampling each trajectory to obtain the same number of points for all of them. The Fourier cumulative curvature descriptor is then used to characterize each trajectory. Only 50% of initial Fourier coefficients is kept in the final descriptor.

5.1 Classification results

We perform a Leave-One-Out cross-validation test using a SVM with a *RBF* kernel. The goal is to evaluate the performance of the method and to assess the interest of characterizing trajectories in the simplex with the Fourier-shape descriptor. A recognition rate of 96.6% is obtained. Table 3 exposes results of the cross-validation test for each activity class. It illustrates the fact that Fourier shape descriptor provides a good characterization of activity trajectories on the semantic hypersphere. Trajectories of the same activities commonly share the same shape and the same sequence of elementary actions. Describing trajectories by Fourier coefficients enables a robust and compact characterization of the shape in the frequency domain. In fact, results remains the same until a removal up to 80% of the coefficients. Figure 5 shows that the global trajectory shape is maintained with only 10% of Fourier coefficients. Moreover, the use of spherical coordinates allows to encode in the descriptor information about elementary actions variation over time, which is a crucial point here.

Activities	High jump	Basketball	BaseBall
High jump	100%	0%	0%
Basketball	0	100%	0%
Baseball	10%	0	90%

Table 3: Confusion matrix when a SVM classifier is trained on activity trajectory features from our method. (`High-Jump`, `Basket-ball` and `Base-ball`). Recognition rate is 96.6%.

The recognition rate obtained with a Leave-one-out cross-validation test emphasizes the discriminative power of this representation. Considering trajectories on the simplex allows to take into account the temporal order of elementary actions for each activity class. In

comparison, we have applied the STIP method provided by [] on videos used in our experiments. The confusion matrix is presented in Table 4. The global recognition rate for the STIP on this set is 86.6%, to be compared with the 96.6% reached by the proposed method. The semantic aspect of our method also allows a better generalization of human activities.

Activities	High jump	Basketball	BaseBall
High jump	100%	0%	0%
Basketball	0	80%	20%
Baseball	0%	20	80%

Table 4: Confusion matrix when a SVM classifier is trained with the STIP method from Laptev []. Recognition rate is 86.6%.

6 Conclusion

We develop in this paper an original approach for human activity recognition. The method characterizes human activities as a sequence over time of elementary actions probabilities. These sequences are then projected as trajectories on a semantic simplex to be characterized using the total curvature Fourier descriptor. The frequency domain allows to encode shape information on trajectories and permits to discriminate between different human activity classes. Unlike generative probabilistic model, the elementary actions which compose human activities are statistically learned with a robust action recognition method trained on a cross-dataset.
Considering human actions as trajectories on the semantic manifold opens the way to different applications, such as video summary by computing a mean shape on the manifold.

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