

Pseudo-3D Trajectories: An Effective Approach for Motion Representation in Depth Data

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Abstract

Leveraging the motion information of trajectories shows the effectiveness to the human action recognition in 2D video. However, the issue is that this approach direction is effective or not when represents motions in 3D video is not still answered. In this paper, we will deal with this issue by conducting experiments based on 2D trajectory features to present motion information from one 3D video representation. Beside, in order to ensure including depth information, we propose a method based on compensating motion information from other representations. Evaluated on the benchmark datasets, our method significantly outperforms the 3D SoA methods.

Keywords: **Trajectory**, action recognition, depth, feature representation

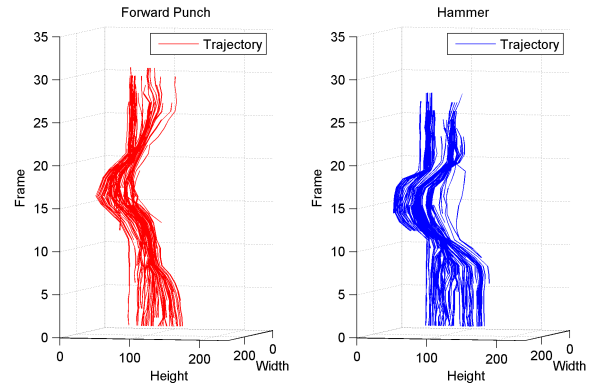
1. Introduction

Background and Challenges. Gần đây, với sự phát triển của RGB-D camera như Kinect, depth data đã mở ra nhiều hướng nghiên cứu tiềm năng cho bài toán Human Action Recognition. So sánh với intensity images thông thường, depth maps hỗ trợ nhiều advantages hơn. Ví dụ, depth maps cung cấp các thông tin về shape rõ ràng hơn so với intensity images. Hơn thế nữa, depth data ít bị ảnh hưởng bởi những thay đổi của ánh sáng. Tuy nhiên, các phương pháp dựa trên intensity liệu có hiệu quả trên depth data hay không vẫn chưa được quan tâm nhiều.

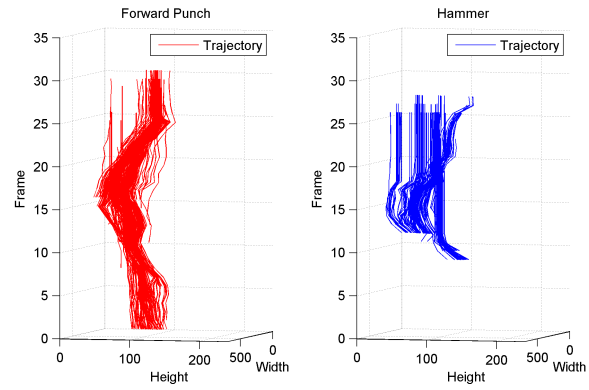
Existing approaches and drawbacks. Trong bài toán action recognition, để adapt các phương pháp dựa trên intensity cho depth data có 2 yếu tố chính. Thứ nhất, để capture motion information hiệu quả việc chọn lựa a robust feature representation là rất quan trọng. Thứ hai, để đảm bảo motion là đầy đủ thông tin trong depth video, việc bổ sung thông tin depth vào feature representation là yêu cầu không thể thiếu. Tuy nhiên, các phương pháp được đề xuất gần đây vẫn chưa hội tụ đủ 2 yếu tố này. Một số phương pháp như [1, 2] xem xét depth value như là intensity value và adapt các intensity-based techniques. Mặc dù, chúng có thể đạt được những kết quả hợp lý, nhưng tất cả chúng đều phải đối mặt với nhiều hạn chế. [DMM-HOG] có thể tận dụng thông tin depth từ các phép chiếu của depth maps. Nhưng its feature representation dựa trên global motion như HOG sẽ dễ gây nhầm lẫn bởi những similar postures. [2] có thể đảm bảo depth information trong việc tính toán features. Nhưng cách tiếp cận này không đảm bảo được sự tin cậy khi extract các local points, do bởi textureless data and depth noise. Ngoài hướng tiếp cận trên, các phương pháp như [3, 4] chỉ tập trung khai thác depth information nên không tận dụng được sức mạnh của các intensity-based features. Do đó, hướng nghiên cứu của chúng tôi là propose một phương pháp có thể đáp ứng đầy đủ cả 2 yếu tố nêu trên.

Proposal, Idea and Steps. Trong bài báo này, chúng tôi sử dụng một feature representation dựa trên dense trajectories của [5], do bởi hiệu quả của cách tiếp
cận này trong nhiều bài toán, including activity recognition and multimedia
event detection. Các trajectories thu được bằng cách tracking các sampled points
densely sử dụng optical flow fields. Sau khi extract trajectories, các trajectory-
aligned descriptors sẽ được adopted. Sau đó, features tính toán được từ các
descriptors này sẽ được sử dụng cho việc biểu diễn motion information trong
video.

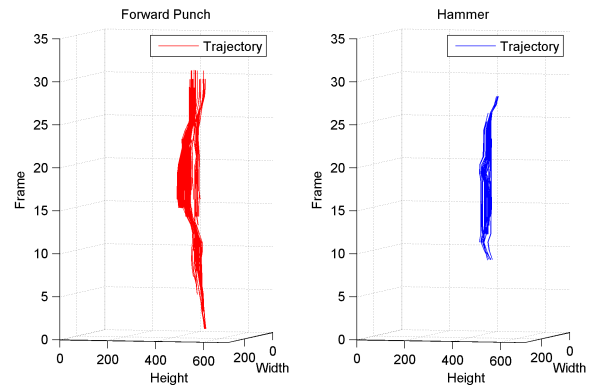
Tuy nhiên, việc thiếu sót depth information trong feature representation có
thể gây ra các trường hợp bị confused, như được chỉ ra trong Figure 1a. Do
đó, để đảm bảo việc không bỏ sót thông tin depth, ý tưởng cơ bản là combine
thông tin chuyển động từ nhiều góc nhìn khác nhau. Các biểu diễn từ nhiều góc
nhìn có thể đạt được bằng cách chiếu depth maps lên trên các mặt phẳng tương
ứng. Việc chiếu này dễ dàng thực hiện được bởi những thuận lợi mà depth data
mang lại.



(a) From front view



(b) From side view



(c) From top view

Hình 1: Minh họa sự tương tự giữa phần lớn các Trajectories của 2 actions: Forward Punch & Hammer.

Experiments and Results. Chúng tôi tiến hành các experiments trên challenging benchmark datasets, các kết quả thí nghiệm chỉ ra rằng phương pháp của chúng
45 tôi đánh bại the SoA methods trên depth data. Các kết quả này đã cho thấy những contributions của our method: (1) We propose an adaptive method for 3D video representation by using 2D features. (2) We thực hiện comprehensive experiments on the state-of-the-art MSR Action 3D dataset and show that our method is the best when compared with the state-of-the-art 3D methods.

50 *Paper structure.* After a brief review of the related work in Section 2, the proposed method is described in Section 3. Section 4 presents the experimental results and their concerned discussions. The summaries of our work are given in Section 5.

2. Related Works

55 2.1. Trajectories Extraction

Trajectories provide a compact representation of motion information in video. Trajectories from intensity videos can be used for multimedia event detection (MED), video mining, action classification and so on. Trajectory extraction much depends on both processes: sampling and tracking. Some concerned meth-
60 ods, such as [6, 7] used KLT tracker [8], or [9] matched SIFT descriptors between consecutive frames to obtain feature trajectories. Recently, the dense trajectories feature proposed by [5] has achieved state-of-the-art performances on MED systems, such as, segment-based system [10] on TRECVID MED 2010, 2011, or AXES [11], and BBNVISER [12] on TRECVID MED 2012.

65 Although, depth data has been studied ago several decades, the trajectory extraction in depth videos is not still paid attention to. This is obviously a significant deficiency for motion feature-based systems using depth data.

2.2. Feature Representation from Depth Videos

In terms of human action recognition in depth video, most recent methods
70 exploit depth information into two major directions. The first one is adapting
intensity techniques-based methods for depth data. The second one is proposing
approaches to use depth value as its mean.

For the first direction, Yang.X et al. [1] propose the Depth Motion Maps
(DMM) to accumulate global activities in depth video sequences. And the His-
75 togram of Oriented Gradients (HOG) are computed from the DMM to represent
an action video. Another approach bases on spatio-temporal interest points pro-
posed by Xia.L and Aggarwal.J.K [2]. In this approach, they extend a work of
Dollar et al. [13] to adapt for depth data.

For the second direction, [14] uses a bag of 3D points to characterize a set
80 of salient postures. The 3D points are extracted on the contours of the planar
projections of the 3D depth map. And then, about 1% 3D points are sampled
to calculate feature. [15, 16, 3] use occupancy patterns to represent feature
in action video. Another approach proposed by Oeifej et al. [4] leverages the
distribution of surface normal orientation in the 4D space of time, depth and
85 spatial coordinates to build a feature histogram. Inspired by results of Shotton
et al. [17] and Xia.L et al. [18], works [19, 3] propose new types of features based
on skeleton information.

Different from other approaches, we use a trajectory-based approach for ac-
tion recognition. We do not care to segment human body like in [14, 1]. We
90 only investigate the benefit of generating intensity representations from depth
data, as mentioned in [14, 1]. Moreover, we leverage the effectiveness of trajec-
tory feature to represent an action video. In our best knowledge, no methods
has previously proposed for human action recognition using depth data. We con-
duct evaluations on recognition accuracy using dense trajectories motion feature
95 proposed by Wang et al. [5].

3. Proposed Method

This paper presents a effective depth video representation by adapting intensity trajectories-based motion features. First, chúng tôi sẽ cung cấp một brief review of the dense trajectories-based feature proposed by Heng Wang et al. [5].
 100 Những phần liên quan như: dense sampling, tracking and feature descriptors is referred to. Our trajectories-based approach for depth data is mentioned at the end of this section.

3.1. Dense trajectories

In order to obtain trajectories, there are two important steps: sampling and
 105 tracking. [5] propose sampling on a dense grid with a step size of 5 pixels. The sampling is performed at multiple scales with a factor of $1/\sqrt{2}$. Then, tracking is the next step to form trajectories. At each scale, in frame t , each point $P_t = (x_t, y_t)$ is tracked to point $P_{t+1} = (x_{t+1}, y_{t+1})$ in next frame $t+1$ by:

$$P_{t+1} = (x_{t+1}, y_{t+1}) = (x_t, y_t) + (M * \omega)|_{(\bar{x}_t, \bar{y}_t)}, \quad (1)$$

110 where $\omega = (u_t, v_t)$ denotes the dense optical flow field, M is the kernel of median filtering, and (\bar{x}_t, \bar{y}_t) is the rounded position of P_t . The algorithm of [20] is adopted to compute the dense optical flow. And to avoid a drifting problem, a suitable value of trajectory length is set to 15 frames. Beside, trajectories with sudden changes are removed.

115 After extracting trajectories, two kinds of descriptors: a trajectory shape descriptor and a trajectory-aligned descriptor can be adopted.

Trajectory Shape Descriptor. This descriptor describes the shape of a trajectory in the simplest way. Given a trajectory of length L , its shape is concatenated by a sequence of displacement vectors $S = (\Delta P_t, \dots, \Delta P_{t+L-1})$, where $\Delta P_t =$
 120 $P_{t+1} - P_t = (x_{t+1} - x_t, y_{t+1} - y_t)$. In order to make the descriptor invariant to

scale changes, the final result is then achieved by normalizing the shape vector by the overall magnitude of the displacement vectors:

$$\bar{S} = \frac{(\Delta P_t, \dots, \Delta P_{t+L-1})}{\sum_{k=t}^{t+L-1} \|\Delta P_k\|}, \quad (2)$$

Trajectory-aligned Descriptor. The descriptors are much more complex than the trajectory shape descriptor. They are computed within a space-time volume (125 $N \times N$ spatial pixels and L temporal frames) around the trajectory. This volume is divided into a 3D grid (spatially $n_\sigma \times n_\sigma$ grid and temporally n_τ segments). The default settings of these parameters are $N = 32$ pixels, $L = 15$ frames, $n_\sigma = 2$, and $n_\tau = 3$.

In order to capture the local motion and appearance around a trajectory, (130 three kinds of descriptors have been employed: the Histogram of Oriented Gradient (HOG) [21], the Histogram of Optical Flow (HOF) [22], and the Motion Boundary Histogram (MBH) [23]. For HOG, orientation information is quantized into 8-bin histogram. HOF is 9-bin histogram. Since the feature of a trajectory is calculated and concatenated from sub-volumes of a 3D volume, the final (135 representation has 96 dimensions for HOG and 108 dimensions for HOF. MBH descriptor computes derivatives on both horizontal and vertical components of optical flow $I_\omega = (I_x, I_y)$. Similar to HOG descriptor, the orientation information is quantized into 8-bin histogram. Since the motion information is combined along two directions, the final representation is $96 \times 2 = 192$ -bin histogram. By (140 presenting gradient of optical flow, MBH descriptor is able to suppress global motion information and only keep local relative changes in pixels.

According to the authors [22, 5, 24, 25], all the three descriptors have shown the effectiveness for action recognition. The experimental settings for these descriptors are based on an empirical study showed in [5]. We also conduct our (145 experiment on all the three descriptors when compared to the depth-based state-of-the-art methods.

3.2. Pseudo-3D trajectory-based Approach for Motion Feature in Depth Data

Our proposed trajectory-based approach for human action recognition in depth data is as follow. At first, intensity representations are formed from the sequence of depth maps, as illustrated in Figure 2. In particular, we choose
150 number of the representations of 3. Number 3 represents 3 view directions: front, side, and top in 3D space. Forming the representations is necessary due to dimensional gap when we adapt 2D techniques for 3D data. After that, the dense trajectories are extracted from the intensity representations. And the
155 feature descriptors are also computed in this step. At the next step, with each intensity representation, corresponding feature representation is quantized from raw trajectory features by apply a "bag-of-words" model. A "late fusion" scheme is used to generate the final feature representation for action in the sequence of depth maps (Fig. 3).



Hinh 2: Illustration on Our Proposed Method



Hình 3: Our Framework Overview

160 In order to generate intensity representations from the sequence of depth
 maps, we use the approach proposed in [14]. This technique is also used in
 [1]. Basically, this method projects depth maps onto three orthogonal planes in
 Casterian space to obtain corresponding intensity representations. However, mo-
 tion representation for human action in the previous approaches is accumulated
 165 from global motion information. Therefore, these approaches must deal with the
 challenges from human segmentation problem in more complicated datasets. In
 contrast to the previous ones, we pay attention to capture local motion in-
 formation for representing human actions. With the approach, we do not care
 the challenges for segmenting human body. To effectively use local motion in-
 170 formation, we leverage the effectiveness of trajectory-based representation. In
 practice, we adopt the dense trajectory-based approach proposed in [5]. Thus,
 motion information in depth data can be reproduced by complementary motion
 information in different intensity representations.

Our proposed trajectory-based approach is compared with the state-of-the-
 175 art methods in human action recognition using depth data. Actually, our ap-
 proach does not care skeleton extraction, which is used as an important factor

in some works, such as [3, 19]. In fact, extracting skeleton exactly is still an unsolved problem, due to the challenges, such as: cluttered background, hardware quality, camera motion, ... Figure 4 illustrates an example case when extract
180 skeleton information.



Hình 4: Results on combinations of representations

4. Experimental Settings

4.1. Dataset

We test our method on MSR Action 3D dataset. This dataset contains 20 actions, as showed in Table 1. Actions are performed by ten subjects for two or
185 three times in the context of game console interaction. In total, there are 567 sequences of depth maps. The depth maps are shot at frame rate of 15 fps. The size of the depth map is 640×480 , we resize into 320×240 to ensure processing efficiency.

ID	Action Name	ID	Action Name
1	high arm wave	11	two hand wave
2	horizontal arm wave	12	side-boxing
3	hammer	13	bend
4	hand catch	14	forward kick
5	forward punch	15	side kick
6	high throw	16	jogging
7	draw x	17	tennis swing
8	draw tick	18	tennis serve
9	draw circle	19	golf swing
10	hand clap	20	pick up & throw

Bảng 1: 20 actions in MSR Action 3D dataset

In order to conduct a fair comparison, we use the same experimental settings as [14, 19, 1, 3, 2, 4]. In the settings, the dataset is divided into three action sub-sets. Each subset has 8 actions (Table 2). The two subsets AS1 and AS2 present that grouped actions have similar movements. The subset AS3 groups complex actions together. For instance, action *hammer* seems to be confused with action *forwardpunch* in AS1 or similar movements between action *handcatch* and action *side boxing* in AS2. As for each subset, we select half of the subjects as training and the rest as testing (i.e. cross subject test).

Action Subset 1 (AS1)	Action Subset 2 (AS2)	Action Subset 3 (AS3)
horizontal arm wave	high arm 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	two hand wave	tennis serve
tennis serve	side-boxing	golf swing
pick up & throw	forward kick	pick up & throw

Bảng 2: The three action subsets used in the experiments

4.2. Evaluation Method

Figure 3 shows our evaluation framework for the trajectory-based features. We perform experiments using the proposed approach and compare with the state-of-the-art methods on depth data. We use the application available online¹ to extract dense trajectories and aligned-features. To quantize a large number of features obtained by densely sampling, the "bag-of-words" (BoW) model is applied. At first, in each intensity representation, we randomly get about 80,000 extracted trajectories for clustering with K-mean algorithm. Then, a codebook of 2000 visual codewords is formed for each. After that, the hard-assignment technique is used to compute histograms of the visual words on the corresponding intensity representations.

Once all the BoW histograms are generated, we adopt the late-fusion scheme with the popular Support Vector Machine (SVM) for classification. In practice, we use the precomputed-kernel technique with the histogram intersection mea-

¹http://lear.inrialpes.fr/~wang/dense_trajectories

surement for the first classification step and apply χ^2 kernel for the next step. In our implementation, we use the libSVM library published online by author² and perform the one-vs-all strategy for multi-class classification. We adopt the format requirements of the library to synchronize the annotation and the data.

215 For testing, the scores of each intensity representation at the first classification step are concatenated to generate the final feature representation as the input of the final prediction. The predicted value is defined as the maximum score obtained from all the classifiers. This score shows that a human action is confused with another or not.

220 5. Experimental Results

This section presents the experimental results from applying our proposed approach on MSR Action 3D dataset. We also report the results on the main intensity representation (i.e. front projection). Beside, an evaluation related to selecting compensation information from other representations will be also mentioned.

225 All the results are compared in terms of the accuracy. The best performance is highlighted in bold.

5.1. Recognize Actions from An Intensity Representation

Table 3 - lists the results from our trajectory-based approach on front representation. Interestingly, the result table indicates that this approach beats all the state-of-the-art methods based on silhouette features [14, 1], skeletal joint features [19, 3], local occupancy patterns [16, 15], normal orientation features [4] and cuboid similarity features [2]. However, the results also show that there is significant difference of the performance among the used feature descriptors.

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²<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>

Method	Accuracy (%)
Bag of 3D Points [14]	74.70
STOP [15]	84.80
EigenJoints [19]	82.33
Random Occupancy Patterns [16]	86.50
Local Occupancy Patterns [3]	88.20
Depth Motion Maps-based HOG [1]	91.63
Histogram of Oriented 4D Normals [4]	88.89
Depth Cuboid Similarity Feature [2]	89.30
Ours	94.53

Bảng 3: Results on front representation using MBH descriptor.

Action Subsets		
AS1	AS2	AS3
92.45	92.04	99.11

Bảng 4: Results on three subsets.

Consider the results on action subsets, we found that 2 subsets AS1, AS2
235 contain many confused actions (Table 4). For example, action-pair "hammer"
and "forward punch" in AS1, or "side-boxing" and "hand catch" in AS2, as
showed in Table 5. When analyzing confused actions, we found that the main
cause is due to similar movements. And, since depth data is textureless, it makes
recognition more difficult. That is a reason why we need compensate information
240 from other intensity representations.

	a02	a03	a05	a06	a10	a13	a18	a20
a02	0.833	0	0.167	0	0	0	0	0
a03	0	0.917	0.083	0	0	0	0	0
a05	0	0.364	0.636	0	0	0	0	0
a06	0	0	0	1.0	0	0	0	0
a10	0	0	0	0	1.0	0	0	0
a13	0	0	0	0	0	1.0	0	0
a18	0	0	0	0	0	0	1.0	0
a20	0	0	0	0	0	0.067	0	0.933

(a) Action Subset 1

	a01	a04	a07	a08	a09	a11	a12	a14
a01	1.0	0	0	0	0	0	0	0
a04	0.083	0.833	0.083	0	0	0	0	0
a07	0	0	0.786	0.071	0.071	0	0.071	0
a08	0	0	0	1.0		0	0	0
a09	0	0	0	0.133	0.867	0	0	0
a11	0	0	0	0	0	1.0	0	0
a12	0	0.133	0	0	0	0	0.867	0
a14	0	0	0	0	0	0	0	1.0

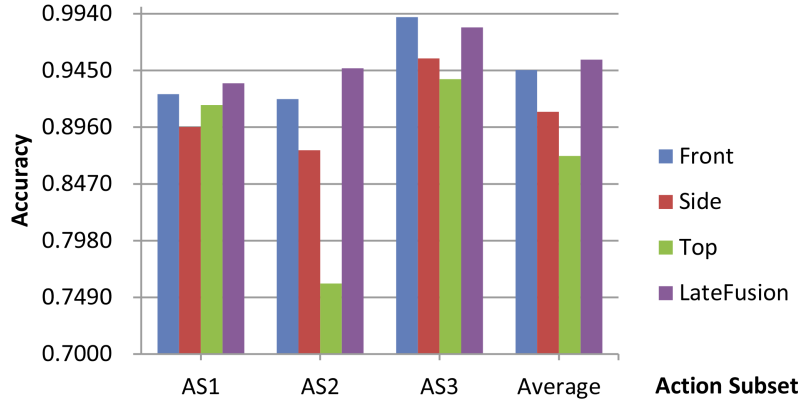
(b) Action Subset 2

	a06	a14	a15	a16	a17	a18	a19	a20
a06	1.0	0	0	0	0	0	0	0
a14	0	1.0	0	0	0	0	0	0
a15	0	0	1.0	0	0	0	0	0
a16	0	0	0	1.0	0	0	0	0
a17	0	0	0	0	1.0	0	0	0
a18	0	0	0	0	0	0.933	0.067	0
a19	0	0	0	0	0	0	1.0	0
a20	0	0	0	0	0	0	0	1.0

(c) Action Subset 3

5.2. Compensate Motion Information from Other Representations

In this part, we conduct experiments based on additional information from all the rest representations compensated for the initial representation. Figure 5 reports a better view in comparing the performance of fusion with separate representations. Expectedly, the fusion performance, which is 0.9543 accuracy, is better than all the separate ones on each representation in terms of average. Obviously, our proposed approach outperforms the mentioned state-of-the-art methods.



Hình 5: Results from using the late fusion scheme on representations

Beside, based on experimental results in figure 5, compensating information shows two confirmations. The first one confirms that recognition result from front representation plays the best role. The second one indicates that compensated information from other representations can support final predictions effectively.

6. Discussions

255 6.1. Evaluate the Role of Intensity Representations

In this section, we consider the role of representations to our proposed method. Figure 5 confirms that front representation achieves the best result. Obviously, it is an indispensable component to merge information. For the rest, we perform experiment on representation combinations with front representation.
260 tion. Experimental results are reported in Figure 6.



Hình 6: Results on combinations of representations

In order to conduct experiment, we create combinations: front and side, front and top. Figure 6 indicates that combination of front and top is better than combination of front and side. Even, the achieved performance is comparable with the performance based on combining all the representations. Actually, combination contains less representations but still ensures good performance is
265 a promising choice to decrease computational cost.

6.2. The Impact of Our Method on Descriptors

For intensity data, according to [5] MBH is the best feature descriptor for dense trajectories. Therefore, in previous experiments, we only use MBH descriptor to represent motion information. Due to the difference between depth data and intensity data, how our approach has influenced other trajectory-aligned descriptors (i.e. HOG, HOF). In this section, we conduct similar experiments on these descriptors to answer this issue.



Hinh 7: Results on trajectory-aligned descriptors

Figure 7 shows interesting results. Although, recognition results on descriptors HOG, HOF are not good for each intensity representation, the final results after fusing have been significantly improved. The results indicate that HOG, HOF also outperform the state-of-the-art methods like MBH. Beside, HOG, HOF have more benefits in decreasing computational cost at processes, such as feature extraction and representation (using the bag-of-words model). This issue means that with simple descriptors we can build an effective and efficient system.

6.3. MSR Daily Activity 3D Dataset

The MSR Daily Activity 3D dataset is proposed by [3], which bao gồm 16 daily activities (Fig. 8) such as talking on the phone, reading a book, playing
285 game, ... etc. In this dataset, background objects and subjects appear at different distances to the camera. Table 6 shows a comparison between the state-of-the-art methods on MSR Daily Activity 3D dataset. In this experiment, we conduct our trajectory-based approach only on front representation. In condition of only using depth data, [3, 4, 2] report a unexpected performance. In [2], they modified
290 this dataset to do evaluation. It is not fair to compare. Therefore, to ensure a fair comparison, we follow a framework similar to [2] and evaluate on original MSR Daily Activity 3D dataset.



Hình 8: Sample Actions on MSR Daily Activity 3D dataset

Although our method outperforms all the state-of-the-art methods, it is not our aim. It is important to note that why in condition of only using depth data, most of methods are failed. When considering failed samples, such as *playing*
295 *a game*, *reading a book*, and *using a laptop*, we found that most of them are confused with action *still*. For *playing a game*, main action focus on motion

of fingers, it is very difficult to discriminate from depth noise. For *reading a book* and *using a laptop*, hand gestures are major actions to present motion information. But it is not fortunately, most of the movements are hidden by interactive objects (i.e. book, laptop). That is one reason to explain for the failure. The second one is performing similar movements with different objects, such as *talking on the phone* and *drinking water*. In these cases, objects is small and textureless. Thus it is very difficult to identify these actions exactly if only depending on depth data.

Method	Accuracy
LOP [3]	42.5
HON4D [4]	52
DSTIP&DCSF [2]	56.88
Ours	62.5

Bảng 6: Performance of Methods on MSR Daily Activity 3D Dataset. Notice that results are reported in terms of only using depth data.

7. Conclusions

We proposed using the trajectory-based approach for human action recognition using depth data in this work. We evaluated our approach by using the dense trajectories motion feature on MSR Action 3D datasets. More interestingly, our proposed trajectory-based approach only applied for one representation beats all the recent state-of-the-art approaches in terms of depth data. Beside, in order to deal with confused actions due to similar movements, compensating information from other representations is proposed. Therefore, the effectiveness of our approach on depth datasets like MSR is confirmed.

A trajectory-based approach with compensating information from separate representations shows promising results. This opens a general approach to lever-

age intensity-based techniques for depth data. This also suggests the importance of trajectory-based motion information on human action recognition using depth data. Therefore, exploiting depth-trajectory-based motion information for human action can be beneficial for an action recognition system. This is also an interesting idea for our future work.

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