MM-SEAL: A Large-scale Video Dataset of Multi-person Multi-grained Spatio-temporally Action Localization

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Abstract

In this paper, we introduce a novel large-scale video dataset dubbed MM-SEAL for multi-person multi-grained spatio-temporal action localization among human daily life. We are the first to propose a new benchmark for multi-person spatio-temporal complex activity localization, where complex semantic and long duration bring new challenges to localization tasks. We observe that limited atomic actions can be combined into many complex activities. MM-SEAL provides both atomic action and complex activity annotations, producing 111.7k atomic actions spanning 172 action categories and 17.7k complex activities spanning 200 activity categories. We explore the relationship between atomic actions and complex activities, finding that atomic action features can improve the complex activity localization performance. Also, we propose a new network which generates temporal proposals and labels simultaneously with adaptively learning the semantic information of proposals, termed Faster-TAD. Finally, our evaluations show that visual features pretrained on MM-SEAL can improve the performance on other action localization benchmarks. We will release the dataset and the project code upon publication of the paper.

1. Introduction

With the increasing number of videos created every day, video understanding becomes more and more indispensable for the computer vision society. How to locate the spatial positions and temporal action boundaries of multi-person in untrimmed videos is a challenging but meaningful task.

In recent years, action recognition and temporal action detection techniques have gained extraordinary breakthrough due to the advent of many large-scale benchmarks, such as HMDB-51[18], Kinetics[17], ActivityNet[2] and HACS[52]. Temporal action detection methods detect actions with boundaries from untrimmed videos, but are unable to spatially detect multiple concurrent human actions. In real-world scenarios, however, it is very common for different people to perform different actions.

Current spatio-temporal localization datasets can be mainly classified into two categories: 1) single-person scene. Datasets such as JHMDB [13], Action Genome[35] and Homage[35]. These datasets have promoted impressive progress for spatio-temporal action localization, but fail to deal with multi-person scenes and are limited to the amount of annotations. 2) multi-person scene. AVA [10] involve multi-subject and provide temporal context for labeling the actions in the keyframe of short clips. Their annotations only cover atomic actions with a constant and short temporal range. TITAN[32] and MultiSports[24] are multi-person datasets and contain fine-grained action categories with dense annotations in both spatial and temporal domains, but they only cover a specific field. Based on the above analysis, there still lacks a large-scale dataset that annotates fine-grained actions in spatial and temporal domains for multi-person scenes in untrimmed daily life videos. On the other hand, the existing spatio-temporal action localization datasets above all aim at actions within 5 seconds, which restricts their application on more complex activities, such as surveillance and healthcare.

To facilitate the development of video understanding, we introduce a novel large-scale video dataset with multi-person multi-grained spatio-temporal annotations among human daily life, dubbed MM-SEAL. We observe that atomic actions can be combined into diverse complex activities. MM-SEAL provides both atomic action and complex activity annotations in tubelet level, producing 111.7k atomic actions spanning 172 action categories and 17.7k complex activities spanning 200 activity categories. As il-
Figure 1. The overview of MM-SEAL dataset. With the help of multi-object tracking, person re-identification, and annotator correction, we obtain tubelets for each subject who are related to the activity. Then we provide complex activities instances and atomic actions instances of each tubelet. In complex activity level, we annotate instances from 200 classes, such as “sumo” marked in green. In atomic action level, we choose atomic actions from the action vocabulary.

Illustrated in Fig. 1, MM-SEAL Atomic Action provide fine-grained atomic actions annotations in spatial and temporal dimensions for multi-person in untrimmed daily life videos. Compared with other similar datasets, we not only annotate spatio-temporal action instances, but also provide short-term trajectories for subject person. It spurs researches on the relation between the target instance and their contexts like nearby instance of the same person or background scene. MM-SEAL Complex Activity are the first to propose a new benchmark for multi-person spatio-temporal complex activity localization, where complex semantic and long duration bring new challenges to spatio-temporal action localization tasks. Compared to datasets (like TITAN, FineGym[38], and MOMA) in the community where both atomic action detection and complex action action detection are proposed, we explore the relationship between atomic actions and complex activities, finding that atomic action features can improve the complex activity localization performance. What’s more, we propose a new network for temporal action detection, which generates temporal proposals and action labels simultaneously with adaptively learning the semantic information of proposals, termed Faster-TAD.

Our contributions are summarized as follows:

1. We develop a new large-scale benchmark MM-SEAL for multi-person multi-grained spatio-temporal detection in human daily life. 25fps frame-wise annotations for MM-SEAL Atomic Action, 4fps frame-wise annotations for MM-SEAL Complex Activity.

2. We observe that atomic actions can be combined into diverse complex activities. Thus, we explore the relationship between atomic actions and complex activities, finding that atomic action features can improve the complex activity localization performance.

3. We propose a baseline for this spatio-temporal localization task. We detect spatial bounding bboxes at the frame-level, and perform temporal action detection. We develop a new network, which generates temporal proposals and action labels simultaneously with adaptively learning the semantic information of proposals, termed Faster-TAD.

4. Our knowledge transfer evaluations show that visual features pretrained on MM-SEAL can improve the performance on other action localization datasets.

2. Related Work

In recent years, some works have developed action classification [8, 4, 27, 34, 39, 42, 43, 44] into temporal action localization [12, 16, 40, 48, 51], and even spatio-temporal action localization [7, 19, 20, 21, 23, 37, 45]. It manifests the trend of video understanding in untrimmed domains.

2.1. Spatio-temporal Action Localization Datasets.

A series of datasets, with spatio-temporal annotations, have been introduced in both single-person and multi-person scenarios. For the single-person scenarios, JH-MDB [13] provide dense spatial localization frame by frame. Action Genome [14] decomposes actions into spatio-temporal scene graphs via sparse sampling. Subsequently, HOMAGE [35] is proposed, equipped with hierarchical activity and atomic action labels. It also provides multiple viewpoints information and captures object relationships in the scene graph. However, temporal localization in HOMAGE is limited to atomic actions, excluding high-level activities. A recently released dataset, TSU[6]
Table 1. Comparison of statistics between existing action detection datasets and our MM-SEAL. (Keyframe with action category and spatial localization in keyframe; Tube with action category, temporal boundary and spatial localization; Segment with action category and temporal boundary; CA denotes the Complex Activity; AA denotes the Atomic Action; * denotes all action partonomy are count together; Instance means the number of instances; Single/multi means proving single person or multi person annotations.

| Dataset       | Action partonomy | Vid.No | Anno type | Act. | Instance | avg. act./ vid.dur. | Scenes | Single/multi |
|---------------|------------------|--------|-----------|------|----------|---------------------|--------|--------------|
| AVA [10]      | -                | 430    | Keyframe  | 80   | 385k     | -                   | human activity | multi        |
| AVA-Kinetics  | -                | 239k   | Keyframe  | 80   | 624k     | -                   | human activity | multi        |
| ActivityNet-1.3 [2] | -        | 19.99k | Segments  | 200  | 23.1k    | 51.4s/1.9m          | human activity | -            |
| HACS [52]     | -                | 50k    | Segments  | 200  | 140k     | 40.6s/2.6m          | human activity | -            |
| FineGym [38]  | action           | 303    | Segments  | 10   | 4.9k     | 55s/2h              | Sports | -            |
|               | sub-action       | 303    | Segments  | 530  | 32.7k    | 1.7s/10m            | Sports | -            |
| UCF101-24 [40]| -                | 15.5k  | Tube      | 24   | 4.5k     | 5.1s/6.9s           | human activity | multi        |
| JHMDB [13]    | -                | 5.1k   | -         | 21   | 0.8k-1.2k| -                   | human activity | single        |
| MultiSports [24]| action   | 197.6k | Tube      | 66   | 37.7k    | 1.0s/20.9s          | Sports | multi        |
| TITAN [32]    | -                | 700    | Tube      | 50   | -        | -                   | egocentric driving | multi        |
| MEVA [5]      | action           | 2.21k  | Tube      | 37   | 66.2k    | -/7m                | surveillance | multi        |
|               | activity         | 536*   | Tube      | 46   | 40.7k*   | -/21m               | smartroom | single       |
| TSU [6]       | atomic action    | 24.4k  | Segments  | 67   | -        | -                   | human activity | multi        |
|               | activity         | 5.4k   | Tube      | 52   | -        | -                   | human activity | multi        |
| MOMA [31]     | atomic action    | 19.3k  | Tube      | 200  | 117.7k   | 12.04s/1.8m         | human activity | multi        |
|               | activity         | 5.4k   | Tube      | 172  | 111.7k   | 3.62s/9.23s         | human activity | multi        |

contains dense annotations including elementary, composite activities and activities involving interactions with objects, performed in a spontaneous manner. TSU [6] is similar to our dataset, but it focuses on smarthome and single-actor scene.

In real-world practical applications, multi-person scenarios are also very common, and a variety of datasets have conducted research in this area. MEVA [5] presents the Multiview Extended Video with spatio-temporal Activities annotations, which aimed at surveillance. The average clip length of MEVA is 5 minutes, but each action is relatively atomic and shorter than MM-SEAL. MOMA [31], has proposed a redefined action parsing for complex human activity recognition. It organizes action categories with four levels. It is worth noting that neither MultiSports nor MOMA are annotated spatially with complex activities, but only with sub-level actions.

2.2. Spatio-temporal action detection method

Most recent approaches based on datasets UCF101-24 and JHMDB can be divided into two categories: frame-level detectors and clip-level detectors. The frame-level detectors [46] detect proposals and actions at the frame-level, and then employ the specific linking strategy to generate instance tubes along temporal dimension. However, frame-level detectors fail to fully exploit temporal context for semantic action classification. In contrast, the clip-level detectors model temporal continuity in the videos. Typical researches, ACT [16] and MOC-detector [25], take a sequence of K frames as input and output K-frame tubelet detection results. The results are linked along temporal dimension into tubes via a common matching strategy. Clip-level detectors can be effectively applied to spatio-temporal localization tasks for atomic actions. However, the number of input frames K, limits the model to capture the features from long-term information. As a result, clip-level detectors can hardly meet the requirements of spatio-temporal localization tasks for activities with complex semantics and long duration.

3. The MM-SEAL Dataset

The purpose of this work is to build a large-scale video dataset for multi-person multi-grained Spatio-temporal Action Localization (MM-SEAL) among human daily life. In this section, we present the data collection process, the statistics, and the characteristics of MM-SEAL.

3.1. Data Collection

3.1.1 Category Selection.

We follow five principles to generate our atomic action vocabulary. Following the method in AVA [10], generality and exhaustivity are both considered. We collect generic actions in daily life and iterate our action list in several rounds. MM-SEAL also follows a principle of fine-grained because some person-object interaction actions have vastly different contexts even within an activity class. For example, there are some activities with intra-class variety such as “cook”. “cook” can be divided into “wash”, “cut”, “grind”, et al. in our dataset. The fourth principle is that our action vocabulary focus on dynamic actions, which means that we only
annotate dynamic actions like "stand up" and "sit down", instead of static pose actions like "stand", "sit". We prefer to focus on patterns of motion, which we think is more valuable. For the last principle, the atomic actions should be visible. We end up with 61 pose actions, 15 person-person interaction actions and 96 person-object interaction actions. On the other hand, complex activity annotations adopt the taxonomy of 200 action classes, taken from ActivityNet-1.3[2].

3.1.2 Data Selection.

For the purpose of obtaining atomic actions and complex activities simultaneously, we randomly choose 5,376 videos from ActivityNet-1.3 and HACS. For complex activity detection, we annotate 17,712 complex activity instances spanning 200 categories in 4,224 videos. For atomic action detection, annotators annotate 111,680 atomic actions instances spanning 172 categories within complex activity instances in 5,376 videos.

3.1.3 Subject Selection.

When multiple subjects are present in a video, only main subjects will be annotated in trainset, ignoring background persons. Subjects are selected whose actions are related to complex activities. For efficiency, we select up to three subjects at the same time period. It should be noted that the subject need to be with head shown in at least one-third of frames. Firstly, we get bounding boxes of persons with a detector[41]. Top 8 boxes with the highest detection confidence in center areas are selected as subjects. Then, these subjects are feed into MOT algorithm[47], generating coarse tubelets. We select the top 50 longest tubelets as the candidate subjects. Thirdly, candidate subjects are shown to annotators. Subject selection follows three principles, being in the central area, having high detection confidence, and being related to complex activities. We annotate actions for each person tubelet in raw videos, allowing duration overlap among subject tubelets.

3.2. Data Annotation

The action annotations of tubelets are given as a set of bounding boxes in each frame, person ID, start time, end time and action category. In this section, we first introduce the labeling process about tubes. Our annotation team is composed of 11 experienced annotators. The annotators are trained for a week before the formal annotation. To guarantee the quality, each video is labeled by an annotator, reviewed by 2 to 6 annotators. The whole annotation process lasts for 1 year.

3.2.1 Spatial Annotation.

We localize a subject spatially with bounding box and distinguish him or her from other subjects with person ID. In order to effectively obtain accurate spatial annotations, we propose a four-step detection method: 1) Using algorithms to get coarse results; 2) Annotators refine results in short-duration; 3) Utilizing person re-identification technology to merge person IDs in long-duration; 4) Annotators refine results in long-duration.

Firstly, we adopt a remarkable detector [41] to get bounding boxes of each person. Then, subject selection in frames is proceeded, which is described in Subject Selection Chapter. We generate coarse person IDs using DeepSORT [47]. In this way, we obtain up to 25 bounding boxes in 1-second of a subject. Secondly, considering that MOT algorithm [47] leads to ID lost or switch in some cases, annotators are asked to refine it within a short atomic action duration. Notably, we find the detector obtaining accurate positions in most cases, while obvious false alarms are discarded. For efficiency, we refine spatial annotation within short atomic action instance duration. Thirdly, person re-identification technology is utilized to merge tubelets in long-duration. We employ a video re-identification model based on the strong baseline [30]. Fourthly, annotators refine results in long-duration. Person IDs that are switched by scene change are not merged.

3.2.2 Temporal and Semantic Annotation.

We provide the start time, end time and semantic labels of action instances. We unify the annotations of repeated actions and actions. For actions that repeat key-moment over a period of time, we define the beginning and ending moment, such as "cut", starting from one second before holding the knife and ending with one second after stopping cutting.

For complex activity localization, we refer to the boundary annotations in ActivityNet-1.3[2] and HACS[52], and adjust the boundaries of actions for each person. Complex activity semantic annotations adopt the taxonomy of 200 action classes, which are taken from ActivityNet-1.3. For atomic action localization, we annotate atomic action instances within complex activity duration. We propose an

| Person 1 action | Person 2 action | Number |
|-----------------|----------------|--------|
| shake legs      | beat with hands| 5298   |
| wave(object)    | bounce         | 3825   |
| twist waist     | dance          | 2815   |
| lift            | walk           | 2277   |
| lift            | run            | 1722   |
| step aerobics   | rotate         | 1587   |
| dance           | bounce         | 1587   |
| dance           | turn to        | 1445   |
| rotate          | dance          | 1441   |
| eat             | clamp          | 879    |
action vocabulary for atomic actions, which is described in Data Collection Chapter.

3.2.3 Quality Assurance.

This subsection proposes many approaches to assure the quality of MM-SEAL. For spatial and temporal annotations, the first priority is to make sure the refined annotation obtained by annotators can be traced in coarse results obtained by the algorithm in forward steps, like step 2 to step 1, step 4 to step 3. Steps are described in “Spatial Annotation” subsection of this Chapter. Then, we propose algorithms to check whether the annotations are out of bounds, and whether the person ID conflicts. Thirdly, in order to check the boundaries for each atomic action instance, we visualize the annotation, which assists annotators to review. Each video will be reviewed by 2 to 6 annotators. For semantic annotations, we adopt a cyclic refinement approach including model discrimination, annotator recheck, annotator refinement, ..., model discrimination, and manual recheck.

3.3. Statistics

MM-SEAL is composed of 5,376 videos in human daily life with 1/5 for testing and others for training and validation.

We present a comparison of dataset statistics between MM-SEAL and some representative video datasets in Table 1. In MM-SEAL, there are 17,712 temporal complex activity instances in 4,224 videos and 111,680 atomic action instances in 5,376 videos. Besides, there are 172 atomic action labels defined in this work and 200 complex activity labels which are the same as ActivityNet-1.3. According to statistics, on average, each video contains 4.78 complex action instances, 21.05 atomic action instances and 3.67 atomic action categories. The distribution of instance duration and instance numbers in each video are shown in Fig. 2. The instance duration of atomic actions is significantly less than that of complex activities, yet the instance number of atomic actions is more than that of complex activities. We also present the distribution of atomic action number, shown in Supplementary Materials.

3.4. Characteristics and Challenges

There are several characteristics of MM-SEAL dataset, which is also challenges on our dataset.

Action hierarchy: MM-SEAL contains 172 atomic actions and 200 complex activities. The intra-class variety in dataset with more fine-grained atomic actions, which helps the detection of complex activity.

Long duration: For MM-SEAL AA, We link recurring actions, which results in the prominence of atomic actions with long duration compared with other datasets focused on atomic action(3.62s vs 1.7s on FineGym vs 1.0s on Multiports). For MM-SEAL CA, 1)the average duration of MM-SEAL(12.04s) is 2.36 times that of UCF101-24(5.1s). 2)The mean instance duration of each CA category ranges from 5.4 seconds to 41.0 seconds.

Diversity: 1)We annotate three action types: Pose actions, person-person interaction actions and person-object interaction actions. There are 39.75% of bounding boxes have at least 1 pose action label, 63.63% of bounding boxes have at least 1 person-object interaction label, which shows that MM-SEAL has rich person-object interaction action instances. 2)rich scenarios, we annotate actions in human activity videos rather than a certain scene.

Complex semantics: 1)On average, each video contains 4.78 complex action instances, 21.05 atomic action instances and 3.67 atomic action categories. 2)multi-person. Table 2 shows the synergy of the actions of different persons in the same key frame. It demonstrates the diversity of behaviors from different people in the same frame, which manifests that multi-person spatio-temporal action detection is of great significance. 3)Movement. We only annotate dynamic actions. We present a figure in Supplementary Materials to illustrates the distribution of bounding box sizes, showing MM-SEAL contains many boxes with small sizes. Figure illustrates bounding box center offset in one second, showing that 50% of boxes offset over 50 pixel. Our densely annotation helps to improve the performance of detecting
Figure 3. Proximity-Category Proposal Block. The first row shows the ground truth segments. The second row is coarse proposals from Proposal Generation Mechanism. The last row shows that the proposal with unsatisfied IoU will be set to a Proximity-Category according to its nearby ground truth segment. For example, proposal 2 has a label of “using the rowing machine - proximity”.

Figure 4. Proposal Attention Module. Proposal features are generated from proposal generation outputs and the shared features by a ROI layer. Then, encoder layer is followed to further encode the proposal representation. Finally, Self and Cross Attention block is applied to model the proposal semantic features.

Figure 5. Auxiliary-Feature Block. Two streams of features go through base module respectively. Then, they are combined along the temporal dimension. The rest of the network keeps the same.

Rich labels in our dataset encourage the researchers to consider temporal action proposal and classification in a single framework.

For the baseline method, we think that the temporal action detection is one of the difficulties, so we focus on this and propose a SOTA network (Faster-TAD). To explore our algorithmic capabilities of temporal action localization, we use gt bboxes as the detected bboxes below. In this way, performance is measured by the average mAP(%) at different tIoU thresholds (0.5 to 0.95 with 0.05 interval). The metric is employed from [15]. Following the standard practice [46, 16], we utilize frame-mAP and video-mAP to evaluate spatio-temporal action detection performance.

4. Baseline Approach

**MM-SEAL** develop two benchmarks: atomic spatio-temporal action detection and complex spatio-temporal activity detection. We propose a baseline for this spatio-temporal localization task. We first detect proposals at the frame-level, then track high-scoring proposals throughout the video using a tracking-by-detection approach. The spatio-temporal action localization task is transformed into temporal action localization task. It should be noted that we only perform semantic classification in the temporal action localization stage, effectively using temporal information.

4.1. Faster-TAD

Current mainstream approaches [28, 33, 50] are multi-step solutions which achieve good performance. They include proposal generation, action classification, ensemble results of classifiers and proposal post-processing. However, they fall short in efficiency and flexibility, especially for videos with diverse semantic labels. In recent years, there are also some works focused on single network [26, 49], but they fail to yield comparable results as those of multi-step approaches.

To simplify the pipeline of TAD, we propose a novel single network with remarkable performance, dubbed Faster-TAD. Inspired by Faster-RCNN [36], we jointly learn temporal proposal generation, action classification, and proposal refinement with multi-task loss, sharing information for end-to-end update.

In classification head, we propose a new Context-Adaptive Proposal Module, which consists of Proximity-Category Proposal Block (Fig 3), Self-Attention Block, and Cross-Attention Block. Self-Attention Block, and Cross-Attention Block are shown in Fig 4, which greatly enhance semantic information for proposals. Context-Adaptive Proposal Module is an efficient attention module, which adaptively learn the semantic information through three aspects.
Many complex human activities have long duration and consist of atomic actions. Action recognition model Swin Transformer[29] is adopted to extract features of each clip as input for subsequent localization task. Nevertheless, action recognition model is trained with trimmed short clips. To address this issue, we adopt atomic features as auxiliary features extracted by Slowfast[8] trained on MM-SEAL Atomic Actions. We designed a feature aggregation method named Auxiliary-Features Block to adapt to the two streams input. As shown in Fig. 5, main and auxiliary features are combined in a simple way after going through two separate base modules.

Extensive experiments demonstrate that Faster-TAD outperforms existing single-network detectors by a large margin on many temporal action detection benchmarks, obtaining state-of-the-art results on ActivityNet-1.3 and SoccerNet-Action Spotting[9]. Algorithmic details and experiments are attached in Supplementary Materials.

4.2. Atomic spatio-temporal action detection

We extract features of raw videos utilizing the Slowfast model[8] with windows = 32, and a stride = 4. Model is trained on our MM-SEAL Atomic Action to get atomic action features. In each window, we use 4fps bounding boxes to extract person features by ROI layer [11]. The final tubelet feature is termed as Slowfast-T. Faster-TAD is employed to obtain boundaries and semantic labels of action instances for each tubelet. Experimental results are given in Table 3. We set MM-SEAL videos belonging to the training set in ActivityNet-1.3 to the MM-SEAL training set.

4.3. Complex spatio-temporal activity detection

We conduct comparative experiments with two configurations, whose results are shown in Table 3. We adopt the released checkpoint of TSP model to extract video features with windows of size=16, stride=2. In each window, we use 2fps bounding boxes to extract person features by an ROI layer [11]. The final tubelet feature is termed as TSP-T. This configuration obtains 67.66% mAP in top120 categories. On the other hand, we adopt Slowfast-T(atomic action feature) as auxiliary features. we concatenate TSP-T and Slowfast-T, obtaining two-stream features as the input for Faster-TAD. Under this configuration, the experiment obtains 68.93% mAP in top120 categories, bringing a mAP gain of 1.27%. Experiments demonstrate that learning the features of atomic actions is helpful for complex activity localization task.

5. Experiments and Analysis

5.1. Metrics

Following the standard practice [46, 16], we utilize frame-mAP and video-mAP to evaluate spatio-temporal localization task.

We evaluate several typical action detection frameworks on MM-SEAL, and compare their performance on UCF101-24 and JHMDB.

As shown in Table 4, MOC-detector and YOWO achieve excellent results in Both UCF101-24 and JHMDB, while getting a poor performance on our MM-SEAL CA. YOWO and MOC-Detector predict bounding boxes and action probabilities directly from video clips. However, they perform poorly when detecting an activity with a long duration which need a large receptive field temporally. On the other hand, compared with other datasets, MM-SEAL contain more complex semantics and more precise temporal annotations. K is defined as number of frames fed to model. We set K as 7 and 11 separately, and find a improvement in performance as K increased.

Unlike UCF101-24, MM-SEAL provide 4fs annotations because of the long duration of complex activity. Each frame is fed into the MOC detector to learn moving point trajectories by estimating movement at adjacent frames on UCF101-24. For complex activity, we feed the model 4fs video frames, which we guess greatly affects the results. Comparing the above method with our baseline, we observe that how to connect trajectories is very important in spatio-temporal action detection tasks with long instance duration.

For our atomic actions, we observe that the frame-MAP of top60(13.88% k=7) is much larger than the frame-mAP of top120(5.78% k=7). The long tail effect of the number of instances between categories has a great influence on the results. UCF101-24 and JHMDB have only the same label of activity for each video, which provides enough characteristic background cues for detectors. Meanwhile, MM-SEAL provide multiple label of actions within a video. Further-
Table 4. Comparison of the state-of-the-art methods on MM-SEAL, UCF101-24 and JHMDB.

| Method               | SEAL-CA | SEAL-AA | UCF101-24 | JHMDB |
|----------------------|---------|---------|-----------|-------|
|                      | $F_{0.5}$ | $V_{0.5}$ | $F_{0.5}$ | $V_{0.5}$ | $F_{0.5}$ | $V_{0.5}$ | $F_{0.5}$ | $V_{0.5}$ |
| YOWO                 | 0.08     | 0.24    | -         | -      | 71.10     | 72.97     | 46.42     | 74.51     | 88.05     | 82.57     |
| MOC(K=7, top60)      | 0.52     | 1.22    | 0.23      | 3.52   | 0.46      | 78.0      | 82.8      | 53.8      | 70.8      | 77.3      | 77.2      |
| MOC(K=7, top120)     | 0.22     | 0.93    | 0.51      | 1.47   | 0.19      | -         | -         | -         | -         | -         | -         |
| MOC(K=11, top60)     | 1.16     | 2.20    | 0.88      | 3.74   | 0.57      | -         | -         | -         | -         | -         | -         |
| MOC(K=11, top120)    | 0.48     | 0.91    | 0.37      | 2.10   | 0.26      | -         | -         | -         | -         | -         | -         |

Table 5. Performance comparison of initialization methods on A V A fine-tuning.

| Method                         | Pre-train Dataset | $T_{50}$ mAP |
|--------------------------------|------------------|--------------|
| Pre-train Kinetics-700         | -                | 29.3         |
| Pre-train MM-SEAL Atomic Action| -                | 30.4         |
| Semi-Transfer MM-SEAL Atomic Action | -                | 30.8         |

Table 6. Action detection results on validation set of ActivityNet-1.3 and HACS, measured by mAP(%) at different tIoU thresholds and the average mAP(%) at different tIoU thresholds (0.5 to 0.95 with 0.05 interval). SF-A means feature extracted by Slowfast [8] trained on our MM-SEAL Atomic Actions.

| Datasets | Feature | 0.5@mAP | 0.95@mAP | Avg mAP |
|----------|---------|---------|----------|---------|
| ANet-1.3 | TSP     | 51.29   | 10.22    | 35.32   |
|          | TSP+SF-A| 52.20   | 10.10    | 35.98   |
|          | Swin    | 57.39   | 10.48    | 39.09   |
|          | Swin+SF-A| 58.30  | 11.28    | 40.01   |
| HACS     | Swin    | 54.13   | 12.02    | 36.92   |
|          | Swin+SF-A| 55.63  | 12.90    | 38.39   |

more, MM-SEAL involves concurrent actions for one person and different people, which bring many challenges for this task.

6. Knowledge Transfer

To demonstrate the effectiveness of MM-SEAL dataset, we have done several spatio-temporal localization knowledge transfer experiments.

6.1. Atomic Spatio-temporal Action Localization

The detailed atomic action annotations possess MM-SEAL with strong generalization capability over other action localization tasks. For example, recent works usually adopt the backbone model pre-trained on Kinetics-700 [3] for downstream tasks fine-tuning. Kinetics-700 is a large-scale dataset which focuses on action recognition. We hope that by sharing the same target on the atomic action localization task, MM-SEAL can play a more active role in improving the model performance on A V A.

We validate the generalization capability of our proposed MM-SEAL dataset to A V A in Table 5. By simply conducting pretraining, MM-SEAL can provide a much better initialization for A V A fine-tuning. To better utilize the consistent target of atomic action localization, we propose to conduct a semi-supervised adaptation process to help the model pretrained on MM-SEAL Atomic Action adapt to A V A dataset. Algorithmic details are attached in Supplementary Materials. The results manifest that assigning proper pseudo labels for A V A allows the model to build better priors for the subsequent fine-tuning.

6.2. Temporal Action Localization

In recent years, researchers have found that the representational capability of input features is very important for the localization task. For example, TSP [1] is an approach focusing on temporally-sensitive pre-training of video encoders. It is observed that atomic actions can be combined into diverse complex activities. We explore the relationship between atomic actions and complex activities by applying atomic action features extracted from raw video to complex activity detection tasks.

Feature extracted by Slowfast [8] trained on our MM-SEAL Atomic Actions is named as Slowfast-A Feature. Swin Feature indicates features extracted by the Swin-Transformer [29] trained on HACS Clips and TSP Feature is trained on ActivityNet-1.3. We adopt Faster-TAD in this task. Slowfast-A Feature is employed as auxiliary features and assembled with TSP Feature or Swin Feature, generating two-stream inputs for localization task.

ActivityNet-1.3 and HACS are commonly adopted to evaluate the capabilities of algorithms on temporally localizing activities in untrimmed video sequences. Extensive experiments are employed on these benchmark, and results are shown in Table 6. We can see that visual features trained on MM-SEAL can improve the performance of other temporal action localization task. What’s more, atomic action features can improve the complex activity localization performance.

7. Conclusions

We develop a new large-scale benchmark MM-SEAL for multi-person multi-grained spatio-temporal detection among human daily life. We are the first to propose a new benchmark for multi-person spatio-temporal complex activity localization, where complex semantic and long duration bring new challenges to video understanding. We observe
that atomic actions can be combined into diverse complex activities, and prove the great effect of the atomic features on complex activity localization task. Also, we propose a baseline method equipped with novel network Faster-TAD and hope our MM-SEAL will spur researches on spatio-temporal action localization tasks. Finally, Our evaluations show that visual features pretrained on MM-SEAL can improve the performance on other action localization benchmarks.

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