Diving Deep into the Motion Representation of Video-Text Models

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Abstract

Videos are more informative than images because they capture the dynamics of the scene. By representing motion in videos, we can represent dynamic activities. In this work, we introduce motion descriptions generated by GPT-4 on three action datasets that capture fine-grained motion descriptions of activities. We evaluated several video-text models on the task of retrieval of motion descriptions. We found that they fall far behind human expert performance on two action datasets, raising this question: Do video-text models understand motion in videos? To address this, we introduce a method of improving motion understanding in video-text models by utilizing motion descriptions. This method proves to be effective on two action datasets for the motion description retrieval task. The results draw attention to the need for quality captions involving fine-grained motion information in existing datasets and demonstrate the effectiveness of the proposed pipeline in understanding fine-grained motion during video-text retrieval.

1 Introduction

Since the large-scale use of contrastive learning to represent images and text (Radford et al., 2021), various efforts have been made to build video-text models (Ni et al., 2022; Luo et al., 2022; Fang et al., 2021; Wang et al., 2021) to relate video to text. Videos provide a way to access the dynamics or motion in the scene that a single image cannot capture. Motion in videos could be due to the action depicted, the effect of camera movement (for example, in egocentric action videos), or a combination of camera motion and action.

We investigate how existing video-text models perceive motion due to the action. For this work, we define motion in action videos as the movement of actors or the movement of actors and objects. The challenge is the lack of datasets that explicitly describe the motion in videos. Figure 1 shows some examples of captions from ActivityNet (Krishna et al., 2017) and MSR-VTT (Xu et al., 2016) datasets. Although verbs are included in captions of multimodal datasets like ActivityNet, MSR-VTT, Howto100M dataset (Miech et al., 2019), Spoken Moments in Time (Monfort et al., 2021), the detailed description of motion is not available. This calls for a need to have an exclusive benchmark to evaluate how video-text models interpret and respond to motion descriptions.

Since motion is very much interlinked to actions, we use human action datasets like Kinetics-400 (Kay et al., 2017), UCF-101 (Soomro et al., 2012), and HMDB-51 (Kuehne et al., 2011) to circumvent the lack of quality annotations of motion descriptions. The advantage of action datasets is that for every action label, we can obtain the corresponding characteristic motion of the action by using large language models like GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI, 2023), which, to a large degree, produce accurate descriptions of motion for each action. In this work, we use GPT-4 to obtain motion descriptions of all the actions in the datasets. Figure 2 shows some examples of the descriptions generated by GPT-4 and corresponding videos and original captions.

We evaluate several video-text models on the motion description retrieval task using the HMDB-51 and the UCF-101 datasets. We compare against human performance and show that all models fall far behind it, raising questions about the design of video-text models and the role of quality captions in training better models to capture human motion. To address this question, we propose a method described in section 4 to investigate if providing better motion description captions helps video-text models understand fine-grained motion descriptions. To validate this fairly, we compare our method with video-text models that similarly initialize their video encoder and text encoder with pre-trained CLIP (Radford et al., 2021) weights so that undue

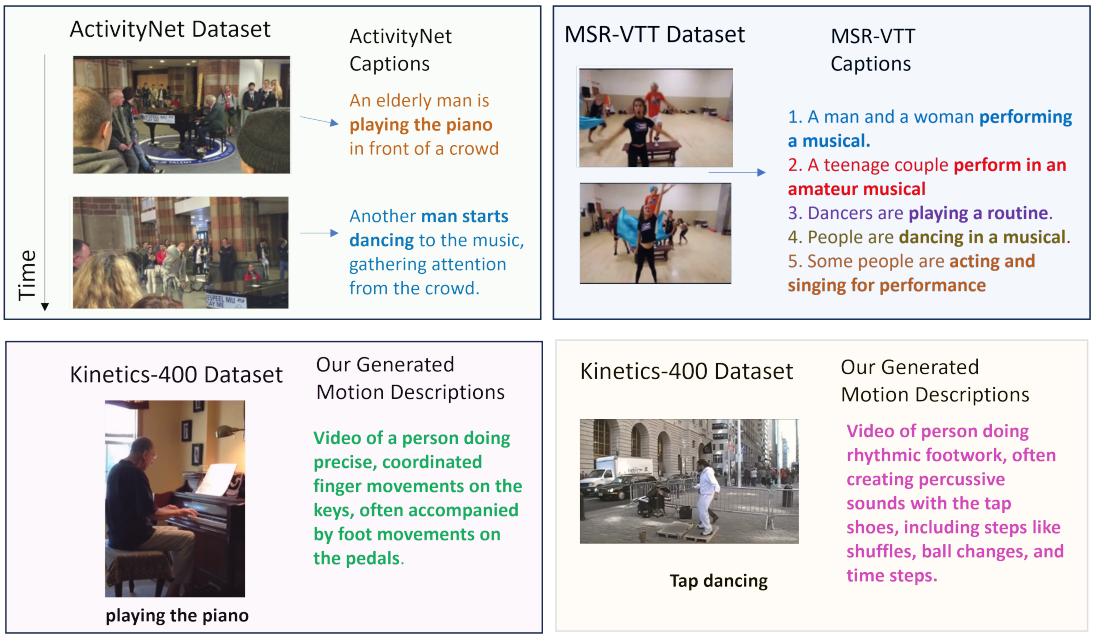

Figure 1: Example captions from ActivityNet, MSR-VTT, and our own GPT-4 generated fine-grained motion description for Kinetics-400 classes. Our descriptions solely describe the motion, whereas other datasets typically use verbs.

performance gain is not obtained by pre-training on video-text data. Our results show that our proposed pipeline is very effective in learning fine-grained motion descriptions on both the UCF-101 dataset and the HMDB-51 dataset. In summary, our contributions are:

1. Creating a dataset of human motion descriptions in three action datasets.

2. Evaluating current video-text models representing motion description in videos on UCF-101 and HMDB-51 datasets and human expert evaluation.

3. Introducing a method to validate the need for better captioning in video-text models to understand motion description and demonstrate the method's effectiveness in capturing fine-grained motion descriptions.

2 Background and related work

Multimodal datasets and video understanding tasks: Howto100M , Spoken moments in time are popular video caption datasets used in pre-training video-text models. ActivityNet , MSR-VTT , DiDeMo (Hendricks et al., 2018) , VaTex (Wang et al., 2019) are some datasets used for video-language alignment tasks like video-to-text retrieval or text-to-video retrieval. To our knowledge, we are the first ones to introduce fine-grained motion descriptions in video datasets, which is not the focus of existing datasets. We introduce motion descriptions on Kinetics-400, HMDB-51 and UCF101 datasets.

Video-text Models: Various efforts have been made to build video-text models (Luo et al., 2022; Fang et al., 2021) mainly for video-to-text retrieval tasks. These models have developed mechanisms to use CLIP and extend it to video frames. Video-text models (Wang et al., 2021; Ni et al., 2022; Wu et al., 2023; Rasheed et al., 2023; Momeni et al., 2023a) have also been used for general video recognition both in supervised and zero-shot action recognition setting. (Momeni et al., 2023a) introduced verb-focused contrastive training to improve the better verb reasoning by learning with hard negative verb examples. (Park et al., 2022) introduced contrast sets to identify pitfalls in video-text models, recommending the need for fine-grained action understanding to tackle hard negatives in contrast sets. We differ from them as we utilize motion descriptions which come up with it's unique challenge. We compare our video-text model with Vanilla CLIP (Radford et al., 2021), XCLIP (Ni et al., 2022), Text4Vis (Wu et al., 2023) and Vifi-CLIP (Rasheed et al., 2023) primarily as they utilize pre-trained CLIP for fair evaluation purposes.

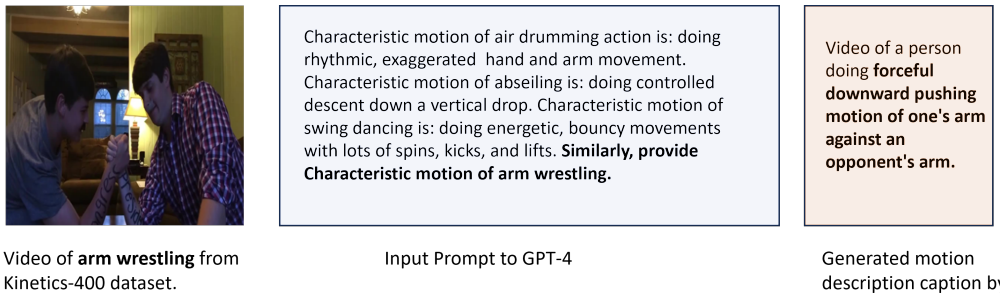

Figure 2: **Schematic representation of the generation of motion descriptions in existing action datasets.**

3 Benchmark

3.1 Designing motion description benchmark:

We perform experiments on Kinetics-400, UCF-101, and HMDB-51 datasets. For each class in these action datasets, we prompt GPT-4 to produce the characteristic motions of the action (given by the caption annotation). Figure 2 shows the overall process of obtaining the motion descriptions. More details about the dataset statistics and generation are described in Appendix D.

We noticed that many of the actions in the UCF-101 and HMDB-51 datasets have objects involved, and the retrieval task is easier when there is an object in the generated motion description. For this reason, we also created another set of motion descriptions where we replaced the names of objects in the motion description with the generic word "object," which made the task slightly more challenging.

4 Proposed Method

In this section, we describe our proposed video-text model that incorporates the textual motion description. A typical vision-language model like CLIP is usually trained using contrastive learning loss or its variations (Miech et al., 2020; Momeni et al., 2023a). The quality of representations learned from the video-text model (Momeni et al., 2023b) will depend on the captions used during pre-training. Since no large video-caption dataset containing motion descriptions exists, we can't directly train a video-text model using contrastive learning. We, therefore, propose a method that utilizes the rich linguistical understanding of motion in actions from GPT-4 to give us the captions required for training. Our approach has two parts: Generating the required motion descriptions of actions using GPT-4 described in section 3 and training video-text models to utilize these motion descriptions described in section 4.2.

4.1 Problem Setting:

The model is trained on kinetics-400 as source dataset D_s and tested on target datasets D_t: UCF101 and HMDB51. The source dataset D_s consists of videos x_s and labels L_s belonging to classes C_s. The target dataset D_t consists of videos x_t and labels L_t belonging to classes C_t. We use a zero-shot setting such that $C_s \cap C_t = \emptyset$. Let the generated motion descriptions from GPT-4 for L_s and L_t be M_s and M_t respectively.

4.2 Architecture Setting:

Figure 3 shows the overview of our approach. While training, we freeze the text encoder from CLIP and fine-tune the visual encoder to learn the motion representation. While testing, motion descriptions are passed through the network to obtain classifier weights. Given a video from the target dataset, we obtain the logits indicating the probability that a video matches the corresponding motion description. Detailed discussion on training, testing, and implementation details is given in Appendix A.

Method	Object	Masked Object
Vanilla CLIP	25.92	23.33
Text4Vis	51.23	33.80
XCLIP	52.37	32.01
ViFiCLIP	52.70	34.76
Our Method	57.02	44.40
Human estimate	98	98

Table 1: Evaluation of percentage accuracy in motion description retrieval task on UCF-101 dataset.

5 Results:

Task: For both the target datasets UCF-101 and HMDB-51, the input is a video and the list of gen-

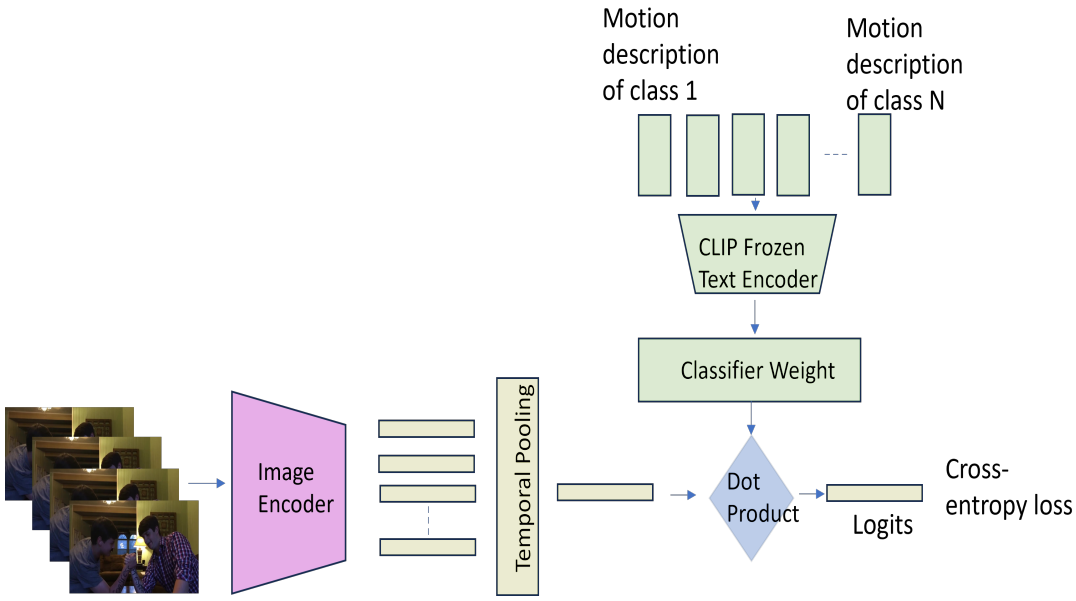

Figure 3: **Schematic representation of our approach encoding motion description in video-text model pipeline:** We integrate motion information as classifier weight in a supervised training paradigm. We finetune the image encoder to integrate the motion information while classifying videos in kinetics400 dataset.

erated motion descriptions for all the classes in the dataset. The video-text model predicts the closest motion description that describes the video. The metric used is the percentage accuracy of correctly predicted motion descriptions.

The models we evaluate are Vanilla CLIP (Radford et al., 2021), XCLIP (Ni et al., 2022), Text4Vis (Wu et al., 2023) and VifiCLIP (Rasheed et al., 2023). Details about the models are given in the Appendix B.

Human estimated performance: We sampled five videos randomly from each class in UCF-101 and HMDB-51. A human expert was asked to select the motion description that correctly describes the video from the list of descriptions generated by GPT4. Human experts are graduate students who have taken computer vision and NLP graduate courses and volunteered for this study.

Table 1 reports the performance of various approaches on the UCF101 dataset. Our proposed method beats previous methods by over 4% for motion descriptions containing the names of objects involved and by over 10% for motion descriptions where the word "object" replaces the object's name. We noticed that all the video-text models perform very poorly compared to human-estimated performance. We also see that video-text models have a strong bias toward nouns. When the specific name of the object involved is not used, there is an average 10% drop in performance for all methods,

Method	Object	Masked Object
Vanilla CLIP	25.26	16.67
XCLIP	29.35	19.35
Text4Vis	34.12	24.93
VifiCLIP	36.20	28.9
Our Method	37.53	26.84
Human estimate	97.5	96

Table 2: Evaluation of percentage accuracy in motion description retrieval task on HMDB-51 dataset.

indicating the strong bias video-text models have for objects. Table 2 reports the performance of various approaches on the HMDB-51 dataset. Similar trends are found in the HMDB-51 dataset.

6 Conclusion

We introduced a benchmark to understand how motion is understood in video-text models. We highlighted the limitations in obtaining quality annotations describing motion in video. We also showed that the performance of video-text models for retrieving motion descriptions is poor compared to human expert performance. Our proposed method circumvents some of these issues and improves over other video-text models. While designing video-text models, we leave it to future work to build better models to capture motion and ignore the biases due to the object or the scene.

7 Limitations

We are using a CLIP text encoder trained on image-text data, to represent motion descriptions. This is not the best thing to do as in practice, the CLIP text encoder would never have encountered the dynamics of videos while training. However, we hope the method works if we replace this CLIP text encoder with any other video-text model text encoder. Another limitation is that we trained on the Kinetics-400 dataset and tested on the UCF-101 and HMDB-51 datasets. As shown in the results section, the presence of an object or scene can often impact the performance during the retrieval task on these datasets. Furthermore, since we are fine-tuning image encoders on the source dataset, there exists the possibility of overfitting the source dataset, leading to poor transferability on another target dataset.

8 Ethical Considerations

We aim to highlight the neglected aspect of modeling motion in video-text models. We think incorporating motion descriptions and reducing the biases of video-text models to objects and scenes positively impacts the design of video-text models. However, there could be a potential risk introduced in our method, as we rely on GPT-4 to provide us with motion descriptions of actions.

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A Implementation details of our method

A.1 Problem Setting:

The model is trained on kinetics-400 as source dataset D_s and tested on target datasets D_t: UCF101 and HMDB51. The source dataset D_s consists of videos x_s and labels L_s belonging to classes C_s. The target dataset D_t consists of videos x_t and labels L_t belonging to classes C_t. We use a zero-shot setting such that $C_s \cap C_t = \emptyset$. Let the generated motion descriptions from GPT-4 for L_s and L_t be M_s and M_t respectively.

A.2 Training:

Motion descriptions M_s are passed through a frozen CLIP text encoder to obtain the class prototypes of L_s. Our intuition is that these class prototypes can be approximated as classifier weights of the supervised video classifier. The concept takes its motivation from the work of (Nukrai et al., 2022; Liang et al., 2022), which shows that text embeddings from CLIP and vision embeddings from CLIP are very similar and fall within a ball of small radius. The obtained CLIP embeddings of motion descriptions from the frozen text encoder would approximately translate to visual class prototypes if obtained visually. With that intuition, we use the class prototypes from the frozen CLIP text encoder as the classifier weights of a visual classifier.

Given a video v_s from the source dataset D_s, T frames are sampled uniformly. The sampled frames are passed through a CLIP pre-trained Image encoder and temporally pooled to obtain a visual feature of the video. Then computing the the dot product of this video feature with the transpose of the classifier weights W_s, the logits are obtained. The model is trained using cross-entropy loss over logits and labels L_s, and the parameters of the CLIP image encoder are updated.

A.3 Testing:

The motion descriptions M_t are passed through the network to obtain classifier weights W_t. Given a video v_t from the target dataset D_t, we obtain the logits indicating the probability that a video matches the corresponding motion description M_t.

A.4 Experimental Details:

Our model uses VIT-B/16 pre-trained CLIP text and image encoder. We use eight frame samples per video. CLIP text encoder is kept frozen during the training and CLIP image encoder is fine-tuned. We train the model for 10 epochs on the Kinetics-400 dataset with a learning rate of 0.00005 with a batch of the size of 20 on 4 NVIDIA RTX A5000 for 40 GPU hours. We use a learning warm step of 5 and a weight decay of 0.2. We use the Adam optimizer with the cross-entropy loss for training

on the Kinetics dataset with a clip ratio of 0.1. Here, we describe more details about our baselines. We report the best results after running experiments on 5 runs.

B Baselines

B.1 Vanilla CLIP:

We use VIT-B/16 pre-trained CLIP text and image encoder obtained from (Radford et al., 2021) and temporally average the frame outputs while evaluating HMDB-51 and UCF-101 datasets.

B.2 XCLIP:

We use XCLIP (Ni et al., 2022) model and code available from https://huggingface.co/docs/transformers/model_doc/xclip. We use "microsoft/xclip-base-patch16-zero-shot" model from huggingface.co while evaluating HMDB-51 and UCF-101 datasets.

B.3 Text4Vision

We use VIT-B/16 base architecture with 8 frames per video. We use pre-trained weights from https://github.com/whwu95/Text4Vis/tree/main

B.4 VifiCLIP

We use VIT-B/16 architecture and obtain the model and code from the official implementation of ViFiCLIP (Rasheed et al., 2023) from https://github.com/muzairkhattak/ViFi-CLIP.

C Dataset

C.1 Kinetics-400

Kinetics-400 is a large-scale dataset containing 400 classes downloaded from YouTube. It has 240K training videos and 20K validation videos. Some videos are missing if the YouTube user has removed them.

C.2 UCF-101

UCF-101 human action dataset from YouTube videos belonging to 101 classes. It has 13K videos. We report results on full classes on one split provided by authors.

C.3 HMDB-51

It contains approximately 7K videos belonging to 51 classes. We report results on the split provided by the authors.

D Motion Description Generation:

To obtain motion descriptions, we use GPT-4 API. The entire generated motion descriptions for the three datasets are provided as supplementary data along with this submission.

We noticed from experiments that we needed to provide some example motion descriptions in the prompt to obtain motion descriptions in the format we are interested in. The prompt we used is "*Characteristic motion of air drumming action is: doing rhythmic, exaggerated hand and arm movement. The characteristic motion of abseiling is: doing a controlled descent down a vertical drop. The characteristic motion of swing dancing is: doing energetic, bouncy movements with lots of spins, kicks, and lifts. Similarly, provide the characteristic motions of action X.*".

D.1 GPT-4 generated motion descriptions quality control:

5 volunteers evaluated the generated motion descriptions for pairwise comparison. The pairwise comparison included selecting the best one among two generated motion descriptions. A vote of majority was used to select the final motion description. Volunteers with diverse experience and age groups were selected to reduce bias.

D.2 Dataset statistics:

The kinetics-400 dataset consists of 400 classes, UCF-101 human action dataset consists of 101 classes and HMDB-51 consists of 51 classes. We generate a characteristic motion description for each class in all three datasets. For UCF101 and HMDB-51, we mask objects manually after obtaining the motion description.