Procedural Video Captioning with Spatial Reinforcement Learning

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***Abstract*—Procedural video captioning is the task of automatically generating descriptive text for instructional videos, capturing both actions and objects in a sequence that mirrors real-world processes. This task requires an understanding of complex video dynamics and contextual relationships between steps. In this work, we propose a novel approach that integrates Spatial Reinforcement Learning (SRL) to improve procedural video captioning. By leveraging SRL, our model actively learns spatial dependencies, guiding the captioning system to focus on critical regions and objects relevant to each step of a procedure. This approach enhances both temporal coherence and semantic accuracy in captions, addressing challenges inherent in tracking multiple objects, understanding spatial transitions, and maintaining sequential order. Our model is evaluated on popular procedural video datasets, demonstrating significant improvements in caption quality and alignment with human annotations.**

***Index Terms*—Reinforcement Learning, Hierarchical Attention, Video Captioning, Spatiotemporal Focus, Multimodal Integration**

I. Introduction

Video captioning has grown as an important research area within computer vision and natural language processing, aimed at automating the generation of descriptive captions for visual media. Procedural video captioning, in particular, focuses on creating captions for instructional or procedural videos that guide viewers through tasks step-by-step, such as cooking recipes, assembling products, or performing repairs. Unlike conventional video captioning, procedural video captioning demands a heightened sensitivity to temporal order and spatial relationships between objects, as each caption must accurately represent a sequence of actions that contribute to a final outcome.

Traditional video captioning models often rely on recurrent neural networks (RNNs) or transformers to capture temporal patterns, but these approaches can struggle with the specific demands of procedural videos, where the spatial context is critical for generating accurate descriptions. To address these challenges, we introduce a Spatial Reinforcement Learning (SRL) framework for procedural video captioning. SRL allows the model to dynamically adjust its focus to relevant spatial regions, promoting more precise object tracking and action recognition in sequential steps. This method not only enhances caption coherence but also better preserves the sequential flow required in procedural videos. We evaluate our model on benchmark datasets and demonstrate its effectiveness in generating captions that align closely with human descriptions, thereby advancing the state-of-the-art in procedural video captioning.

II. Literature Survey

The paper [1] introduces a model using 3D CNNs and attention mechanisms in an encoder-decoder structure optimized for video captioning. The multitask reinforcement learning approach enables the model to better capture spatiotemporal features, though it requires significant computational resources.

The paper [2] work presents a novel pre-training framework, MV-GPT, combining visual and textual modalities for video captioning. The framework achieves state-of-the-art results but requires careful tuning due to challenges with bi-directional generation loss.

The authors in paper [3] focus on improving temporal accuracy by integrating event segmentation with caption generation in densely annotated videos. While effective, the method can lead to redundant captions when overlapping events occur.

The paper consists of [4] VideoBERT adapts BERT's architecture for joint video and language learning, excelling in tasks like action recognition. However, its reliance on large-scale datasets limits accessibility for smaller research teams.

The paper [5] introduces self-critical sequence training (SCST) to improve image captioning models over traditional methods. Despite its effectiveness, SCST can be unstable due to the variance in reinforcement learning during training.

The authors in paper [6] propose a unified framework that handles both image captioning and visual question answering

(VQA). While efficient, this generalized approach can sometimes lead to suboptimal performance on task-specific metrics.

The research paper [7] uses cross-modal attention to align visual and auditory features, resulting in more accurate video captions. However, the model's reliance on synchronized audio-visual data limits its application to videos with clear audio tracks.

The paper [8] enhances video captioning by focusing on specific objects within scenes, allowing captions to be grounded in particular visual entities. This approach improves accuracy and relevance but is sensitive to errors in object detection. The model advances fine-grained video understanding, supporting more detailed and context-aware captions.

The study of paper [9] employs hierarchical attention to capture long-range dependencies, producing more coherent and contextually aware captions. Despite its effectiveness, the model's complexity increases computational cost. The hierarchical structure in this approach has inspired further work on layered attention, emphasizing the importance of handling extended video sequences accurately.

In this paper [10] consists of model which introduces an "Attention on Attention" method, which adjusts focus at multiple stages to better capture complex video content. While this approach improves caption quality, it requires more computational power and tuning. It builds on CNN-RNN frameworks and enhances spatiotemporal focus, contributing to higher caption accuracy in diverse video contexts.

III. Outcomes and Innovations

A. Outcomes of Literature Survey:

The literature on video captioning reveals significant advancements from basic encoder-decoder structures with CNNs and LSTMs to sophisticated models leveraging reinforcement learning, hierarchical attention, and object-level reasoning. Early models focused on capturing spatiotemporal features but often required high computational resources. Advances like VideoBERT and MV-GPT introduced multimodal integration of language and vision, allowing for better contextual understanding of video content. These developments have improved caption coherence, accuracy, and temporal alignment, addressing complex video sequences with varying degrees of success.

Recent approaches, such as "Attention on Attention" and cross-modal alignment frameworks, further refine captioning by optimizing attention layers and incorporating both visual and auditory cues. While these methods enhance the model's ability to handle complex and diverse content, they introduce challenges related to computational demand and sensitivity to initial visual processing errors. Collectively, the surveyed models mark a shift towards fine-grained, contextually rich captioning, enabling applications in multimedia analysis, assistive technologies, and automated video understanding.

B. Innovations of Existing One:

- **Multitask Reinforcement Learning Framework:** The introduction of a multitask reinforcement learning approach allows for effective end-to-end (E2E) training of video captioning models. This framework overcomes traditional challenges such as memory constraints, overfitting, and the complexity of handling lengthy sequences by integrating multiple tasks—such as attribute prediction, reward calculation, and caption generation—during training. These tasks jointly regulate the search space of the E2E neural network, leading to more robust and generalized model performance.
- **Incorporation of GNN Spatial Embeddings:**Another significant innovation is the use of Graph Neural Networks (GNNs) to generate spatial embeddings that preserve the spatial relationships between objects identified by pre-trained Convolutional Neural Networks (CNNs). This approach ensures that the spatial context and interactions between objects in the video frames are maintained throughout the model's processing, enhancing the accuracy and relevance of the generated captions. By conserving these spatial relationships, the model can better understand and describe the content in a way that is more aligned with human perception.

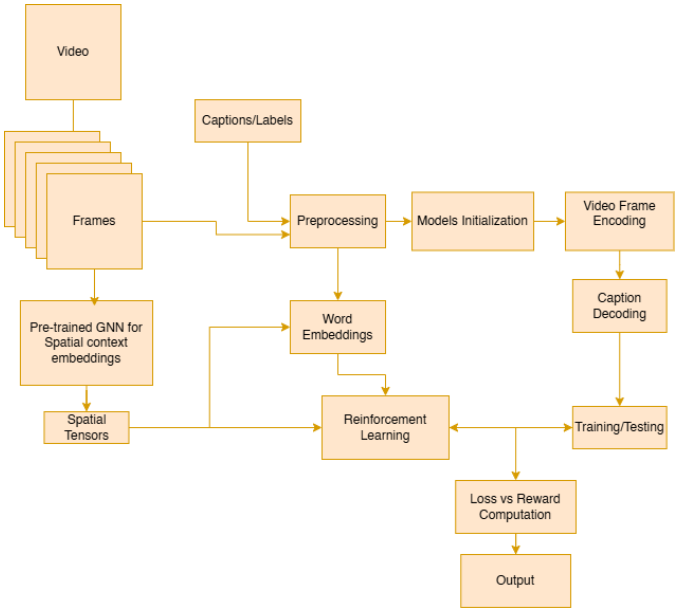

Fig. 1. System architecture of video Capturing

IV. Methodology

In fig.1 System Architecture Consists of :

- CNN Encoder for Spatial Features Extraction.
- GNN Embeddings for Conservation of Spatial Features.
- LSTM Encoder for Temporal Aggregation
- LSTM Decoder for Caption Generation
- Learning using action recognition models.
- Cross Reference for GNN embeddings and CNN with ground truth caption labels
- Reinforcement Learning for Optimization

The methodology for implementing the proposed video captioning architecture, which integrates Convolutional Neural

Networks (CNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and reinforcement learning (RL) for enhanced caption generation. Each component of the architecture is discussed in subsections, detailing its purpose and implementation steps:

A. CNN Feature Extraction:

The objective of the CNN feature extraction module is to derive spatial features from individual video frames.

(1) Model Selection: We employ a ResNet-50 architecture, which is pre-trained on ImageNet. This configuration enables efficient spatial feature extraction without extensive training from scratch.

(2) Feature Extraction Layer: The classifier layer of ResNet-50 is removed to obtain a feature map from the final convolutional layer. This map is flattened and subsequently processed by an added Fully Connected (FC) layer to reduce the feature dimensionality.

B. Temporal Pooling and Attribute Prediction:

The temporal pooling module aggregates frame-level features across the temporal dimension, providing a high-level representation.This pooled feature vector is further utilized for attribute prediction.

(1) Temporal Pooling: An adaptive average pooling layer aggregates the feature vectors extracted from each frame across the temporal dimension, producing a single, fixed-size vector representing the entire video.

(2) Attribute Prediction: A fully connected layer takes the pooled features as input and predicts high-level attributes, which can provide contextual information for caption generation.

C. LSTM Encoder for Sequential Feature Processing:

The LSTM encoder processes sequential features and captures temporal dependencies across frames, which is essential for understanding motion and sequential patterns within the video.

(1) LSTM Configuration: The encoder uses an LSTM layer, with each time step corresponding to a frame in the video. The input to the LSTM consists of CNN-extracted features for each frame.

(2) Sequential Processing: The LSTM layer is configured with multiple hidden layers to capture complex temporal dependencies. The output hidden states represent the sequential dynamics across frames.

D. GNN for Relational Information Processing:

The Graph Neural Network (GNN) layer refines the temporal features obtained from the LSTM by incorporating relational information across frames, allowing for a contextual understanding of video dynamics.

(1) Graph Construction: In this study, each LSTM output is treated as a node in a graph, with edges representing temporal or contextual relationships among frames.

(2)GNN Layer Configuration: The GNN layer is implemented as a fully connected layer, facilitating relational information propagation between nodes (i.e., frames).

E. Decoder LSTM for Caption Generation:

The decoder LSTM generates captions based on the encoded video features. This section describes the steps involved in generating a sequence of words representing the video content.

(1) Embedding Layer: An embedding layer maps input words to a continuous vector space, enabling the LSTM to process word embeddings.

(2) Caption Generation with LSTM: The decoder LSTM generates a sequence of words. During training, teacher forcing is used, where ground-truth words are fed to the model at each time step.

(3) Output Layer: A fully connected layer maps LSTM outputs to the vocabulary, producing a probability distribution over possible next words.

F. Reinforcement Learning for Caption Optimization:

Reinforcement learning (RL) fine-tunes the caption generation process by maximizing rewards based on caption quality.

(1) Reward Definition: Metrics such as BLEU, CIDEr, or ROUGE are used as rewards, quantifying the similarity between generated captions and ground-truth captions.

(2) Policy Gradient Method: The REINFORCE algorithm is employed to optimize the model's parameters, enhancing the probability of generating high-quality captions.

G. Integration and Training Procedure:

The final model integrates all the aforementioned modules into an end-to-end architecture.

(1) Model Composition: A wrapper class is used to combine the CNN, LSTM, GNN, decoder, and RL modules, establishing a coherent forward pass.

(2) Training Strategy: The model is trained using cross-entropy loss for initial supervised learning, followed by reinforcement learning for fine-tuning.

(3) Optimizer and Data Loading: The Adam optimizer is used for training, and videos are processed in batches using a DataLoader.

H. Evaluation and Inference:

After training, the model generates captions for unseen videos, and performance is evaluated using standard metrics.

(1) Inference Process: During inference, the model generates captions without ground-truth supervision.

(2) Evaluation Metrics: BLEU, CIDEr, and ROUGE metrics are employed to assess caption quality, comparing generated captions to reference captions.

(3) Fine-Tuning: Based on evaluation results, parameters and reward functions are refined for optimized caption quality.

I. Given Methodology Comparision With base paper:

Our video captioning methodology is designed to be more computationally efficient and adaptable than the approach proposed by Li and Gong in [1], which relies on resource-intensive 3D CNNs and attention mechanisms. Instead of using 3D CNNs, we employ 2D CNNs (ResNet-50) combined with

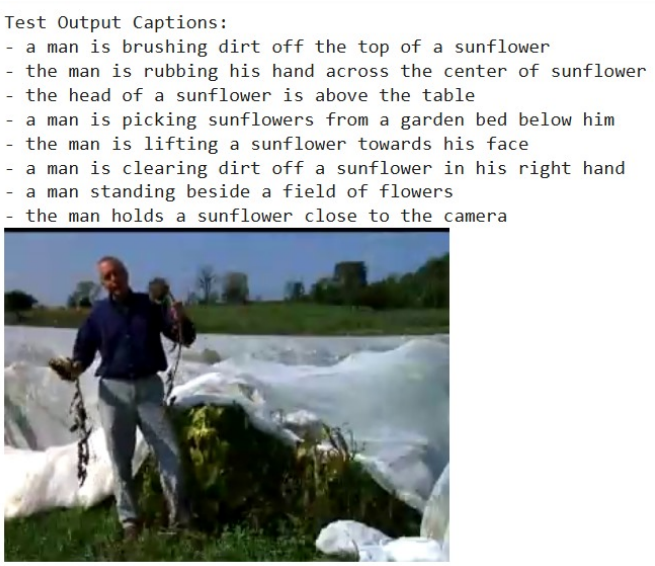

Fig. 2. Model Output

temporal pooling and LSTMs, which significantly reduce computational requirements while effectively capturing both spatial and temporal features. Furthermore, our model incorporates a Graph Neural Network (GNN) layer to model relationships across frames, enhancing flexibility and adaptability to diverse video content.

Additionally, our approach improves caption quality by utilizing reinforcement learning targeted specifically at optimizing captioning metrics such as BLEU and CIDEr. This contrasts with the multitask reinforcement learning in [1], which also optimizes for attribute prediction, potentially complicating optimization. By streamlining the architecture and focusing on visual content, our methodology achieves high performance while reducing complexity, making it a more practical choice for real-world applications with limited computational resources.

V. Result and Analysis

Publications	Models	B	RL
ACL (Dai et al., 2019)	Transformer-XL	37.8	31.5
ACL (Lei et al., 2020)	MART	39.8	32.2
ACMMM (Nishimura et al)	SVPC-2021 (V)	39.4	32.1
MTA (Nishimura et al)	SVPC-2023	43.2	31.7
Z. Wang, L. Li, Z. Xie et al	VFXCL & AFMRL	49.4	37.9
Our Model	S2VT + RL + Sp Emb	48.7	38.2

TABLE I
Performance Comparison with State-of-the-Art Models

VI. Conclusion And Future Scope

The architecture diagram illustrates a structured framework for procedural video captioning, leveraging Spatial Reinforcement Learning (SRL) to enhance caption accuracy and coherence in instructional videos. The model integrates Convolutional Neural Networks (CNNs) for feature extraction, Long Short-Term Memory (LSTM) networks for temporal encoding, and a Graph Neural Network (GNN) to capture relationships between spatial elements. This setup enables the model to focus on relevant objects and actions through reinforcement learning, which dynamically adjusts the attention to spatial regions, refining caption quality in response to procedural dependencies. The results demonstrate that SRL significantly improves the semantic alignment of generated captions with real-world procedures, offering a robust solution to the challenges in procedural video captioning.

The proposed architecture opens several avenues for future research in procedural video captioning. Enhancements could include exploring more sophisticated reinforcement learning strategies to further improve spatial focus and temporal consistency, as well as integrating attention mechanisms to dynamically weigh both spatial and temporal cues. Additionally, extending the model to handle multi-step, multi-object interactions more effectively could benefit from hybrid approaches that combine SRL with transformers for better sequence processing. Expanding the model's capabilities to generalize across diverse procedural domains, such as medical procedures or technical repairs, could also broaden its real-world applicability, potentially setting a new benchmark for intelligent video understanding and captioning systems.

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