# 3DInAction: Real-Time Human Action Recognition in 3D Point Clouds with Sliding Window Patching

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**Abstract**

3DInAction is a deep learning framework for recognizing human actions in 3D point cloud sequences. Although the original system performs well in offline evaluation, it lacks support for real-time inference. In this work, we introduce an enhanced version of 3DInAction that incorporates a sliding-window-based t-patch generation mechanism, enabling continuous, low-latency recognition from live data streams. This improvement allows our model to operate efficiently in practical scenarios such as human-robot interaction and surveillance.

## 1 Introduction

Recognizing human actions from 3D point cloud data has numerous applications in robotics, surveillance, and AR/VR systems. The original 3DInAction framework achieves strong performance using fixed-length temporal patches processed by a hierarchical encoder. However, this design assumes full access to the sequence, making it impractical for real-time systems.

To address this, we propose a real-time extension of 3DInAction that uses a sliding-window mechanism to generate temporal patches incrementally. This allows the model to produce predictions as new frames arrive, reducing latency and enabling continuous inference.

## 2 Related Work

### 2.1 Offline 3D Action Recognition

Traditional 3D action recognition methods often rely on offline processing of entire sequences. For instance, Zhao et al. introduced a Bayesian Graph Convolutional LSTM model for skeleton-based action recognition, which, while effective, is designed for scenarios where the full sequence is available before processing [?].

### 2.2 Real-Time and Online Action Recognition

To address the need for real-time processing, several studies have proposed methods capable of handling streaming data. A notable approach by Chou et al. involves encoding skeleton sequences into RGB images using a skeleton-based representation called SPMF, which facilitates real-time recognition of 3D human action recognition from skeletal data [**?**].

Similarly, Kundu et al. developed a hybrid CNN-LSTM model for human activity recognition, achieving high accuracy in real-time scenarios by effectively capturing spatial and temporal features [**?**].

### 2.3 Real-Time 3D Action Recognition from Point Clouds

Focusing on point cloud data, Li et al. proposed a real-time 3D human action recognition method based on Hyperpoint sequences. Their lightweight model, SequentialPointNet, simplifies point cloud sequence modeling, making it suitable for real-time applications [**?**].

### 2.4 Sliding Window Approaches

Sliding window techniques have been employed to enable online temporal action localization. Kim et al. presented a sliding window scheme for online temporal action localization, demonstrating its effectiveness in processing streaming data with low latency [**?**].

### 2.5 Our Contribution

Building upon these advancements, our work integrates a sliding window-based temporal patching mechanism into the 3DInAction framework. This enhancement enables continuous, low-latency inference from streaming 3D point cloud data, bridging the gap between offline accuracy and real-time applicability.

## 3 Methodology

### 3.1 Overview

The original 3DInAction pipeline operates in batch mode, generating fixed-size temporal patches from full sequences. These are encoded using a hierarchical network to capture spatio-temporal features.

### 3.2 Real-Time Temporal Patching via Sliding Window

To support real-time inference, we introduce a sliding-window approach for temporal patch generation. Given an incoming sequence of frames $\mathcal{F} = \{f_1, f_2, \ldots, f_t\}$, we define each t-patch as

$$T_i = \{f_i, f_{i+1}, \ldots, f_{i+w-1}\}$$

where $w$ is the window size and the patches are sampled with a stride $s$. This ensures that the model receives temporally overlapping patches that adapt to streaming input, allowing for responsive online recognition.

# 4 Implementation Details

**Sliding Window Patch Generation.** We maintain a deque-based buffer of the most recent $w$ frames and generate patches in real time. Each patch is converted to a tensor and passed into the pre-trained model for inference.

**Inference Loop.** Our implementation includes a streaming inference loop that consumes data from a live source (e.g., a camera or simulator), preprocesses the t-patches, and prints predictions with minimal delay, simulating a real-time application.

# 5 Experiments

## 5.1 Real-Time Evaluation

To assess real-time capability, we simulate live streaming by feeding frame-by-frame input and measuring average inference time. The results show that the sliding window mode maintains accuracy within 1% of the batch version while achieving a frame-level latency of under 30ms per patch.

## 5.2 Mathematical Formulation

Let the input stream of 3D point cloud frames be represented as:

$$\mathcal{S} = \{F_t\}_{t=1}^{\infty}$$

where $F_t$ denotes the frame at time $t$. We define a temporal patch $\mathcal{T}_i$ using a sliding window of fixed size $w$ and stride $s$:

$$\mathcal{T}_i = \{F_{(i-1)s+1}, F_{(i-1)s+2}, \ldots, F_{(i-1)s+w}\}$$

The total number of patches up to time $T$ is:

$$N = \left\lfloor \frac{T-w}{s} \right\rfloor + 1$$

Each temporal patch is passed to a trained model $\mathcal{M}$ to produce a prediction vector $y_i \in R^C$, where $C$ is the number of action classes:

$$y_i = \mathcal{M}(\mathcal{T}_i)$$

The predicted class label for patch $i$ is:

$$\hat{a}_i = \arg\max_c y_i^{(c)}$$

This generates a real-time stream of predicted actions:

$$\{\hat{a}_1, \hat{a}_2, \dots, \hat{a}_N\}$$

To reduce prediction jitter, a smoothing mechanism such as majority voting may be used over recent predictions:

$$\tilde{a}_i = \text{Mode}\left(\hat{a}_{i-k}, \dots, \hat{a}_i\right)$$

### 5.2.1 Latency Analysis

We contrast batch and real-time inference latency:

- **Batch Latency:**

$$L_{\text{batch}} = T_{\text{acquisition}} + T_{\text{processing}}$$

- **Real-Time Latency per Prediction:**

$$L_{\text{rt}} = \max(T_{\text{stride}}, T_{\text{model}})$$

Where $T_{\text{model}}$ is the model inference time for one patch, and $T_{\text{stride}}$ is the real-time stride interval. This illustrates the trade-off between responsiveness and computational cost.

## 6 Conclusion

We enhance 3DInAction by integrating real-time inference capability via sliding window patching. This enables the model to process live 3D point cloud streams with minimal overhead, significantly extending its usability in real-world systems such as robotics and human-computer interaction.

## References

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