Part B: Fine Grained Event-Based Human Activity Recognition via Few-Shot

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***Abstract*—This report describes the implementation of a pipeline for the event-based technique - Implements Few-Shot Learning for activity classification using Prototypical Networks. It proposes ways of avoiding catastrophic forgetting by preserving support prototypes and evaluating the performance on support and query sets. The data in Part B was captured in the AV Lab using a neuromorphic Dynamic Vision Sensor (DVS) camera connected via ROS2. Events were extracted and changed into video frames for input to the model. The report describes methodology, results, and insight gained for Part B of the project.**

I. Introduction

The objective of the following report describes a pipeline developed to address fine-grained human activity recognition using Few-Shot Learning (FSL). Event-based data processing represents a new family of transformative technologies, allowing efficient and accurate perception in dynamic, real-time scenarios. Human activity has been recorded in the AV Lab using a neuromorphic Dynamic Vision Sensor (DVS) camera connected with a laptop via ROS2. The events were converted into videos and frames, enabling activity classification based on Prototypical Networks. This approach helps avoid catastrophic forgetting and assesses recognition performance under different shot sizes.

A. Literature Review

In the last decade, event-based learning has undergone fantastic changes. Efforts to emulate biological systems for speed and energy efficiency in processing data in dynamically changing environments have been at the forefront. Herein we review the major works related to visual tracking and Few-Shot Learning.

1) Few-Shot Learning: Foundations and Applications

Few-Shot Learning addresses the challenge of training models on limited labeled data, often utilizing meta-learning strategies.

- Snell et al. [1] proposed Prototypical Networks, a metric-based approach where classes are represented as prototypes in embedding space.
- Finn et al. [2] introduced Model-Agnostic Meta-Learning (MAML), which quickly adapts models to new tasks through parameter initialization.
- Ravi and Larochelle [3] developed optimization-based meta-learning models that leverage memory-augmented networks for efficient adaptation.

2) Neuromorphic Sensing in FSL

Event-based sensing has shown potential for few-shot tasks due to its sparse and high-temporal-resolution data representation.

- Maqueda et al. [4] introduced event-based representations for motion estimation, later adapted for classification tasks.
- Liu et al. [5] extended Prototypical Networks to neuromorphic data, enhancing classification accuracy by effectively handling event streams.

3) Mitigating Catastrophic Forgetting

Catastrophic forgetting, where new information overwrites prior knowledge, is a critical issue in Few-Shot Learning.

- Kirkpatrick et al. [6] introduced Elastic Weight Consolidation (EWC), penalizing updates that interfere with important parameters.
- Lopez-Paz and Ranzato [7] proposed Gradient Episodic Memory (GEM) to incorporate past experiences into gradient updates.

II. Methodology

The pipeline for this project was designed to enable fine-grained activity recognition using Few-Shot Learning and neuromorphic sensing.

1) Data Acquisition in the AV Lab

A Dynamic Vision Sensor (DVS) camera was used to capture event-based data corresponding to human activities, such as walking, jumping, and boxing. The camera was connected to a laptop via the Robot Operating System (ROS2) framework. The real-time event data was streamed as ROS2 topics, providing a high-temporal-resolution representation of activity dynamics.

2) Event Extraction and Video Conversion

The events were extracted from recorded topics. The raw events obtained were converted to videos for interpretation. Each segment in the video related to a particular activity and was further decomposed into individual frames, which were used in the Few-Shot Learning model.

3) Few-Shot Learning Framework

The FSL framework leverages Prototypical Networks for activity classification. It contains the following architecture:

1) **Feature Extraction:** The model uses a convolutional neural network (CNN) comprising several convolution, batch normalization, and ReLU activation layers to learn discriminative features from input frames. The CNN transforms input frames into a compact embedding space, ensuring robust representations for classification.
2) **Prototype Computation:** For each activity class, the support set embeddings are averaged to compute a prototype vector:

$$c_k = \frac{1}{|S_k|} \sum_{x_i \in S_k} f_\phi(x_i),$$

where S_k represents the support set for class k, and f_ϕ is the feature embedding function.
3) **Classification:** Query embeddings are classified based on their Euclidean distance to the class prototypes:

$$d(c_k, q) = \sqrt{\sum_i (f_\phi(q_i) - c_k)^2}.$$

The query is assigned to the class with the smallest distance.

4) Addressing Catastrophic Forgetting

Catastrophic forgetting is addressed through:

1) **Prototype Preservation:** Retaining support prototypes during training and evaluation.
2) **Feature Space Regularization:** Preventing significant distortions in the embedding space.
3) **Balanced Query Updates:** Gradually incorporating new query information while retaining earlier knowledge.
4) **Reinforcement of Key Features:** Ensuring robust embeddings via a CNN extractor focused on motion dynamics.

5) Evaluation Metrics and Scenarios

The framework was evaluated under varying shot sizes (5-shot, 10-shot, 20-shot) for different activity classes. Two primary metrics were used:

1) **Support Test Accuracy:** Measures the classification accuracy on the support set.
2) **Query Test Accuracy:** Measures the classification accuracy on unseen query examples.

6) Visualization of Recognition Performance

The recognition performance for each activity is visualized in Figures 1, 2, and 3, showing the effect of increasing shot sizes on support and query accuracies.

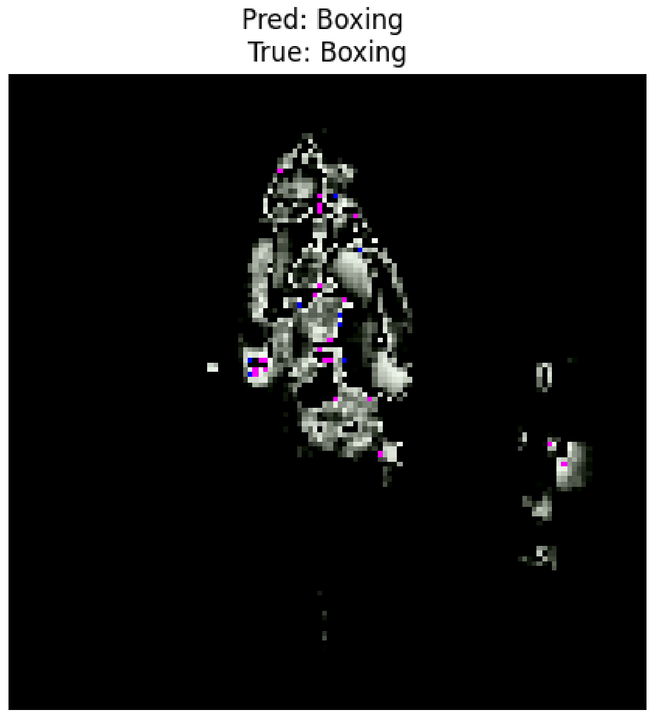

Fig. 1: An Example of a Successful Recognition of Boxing Instance

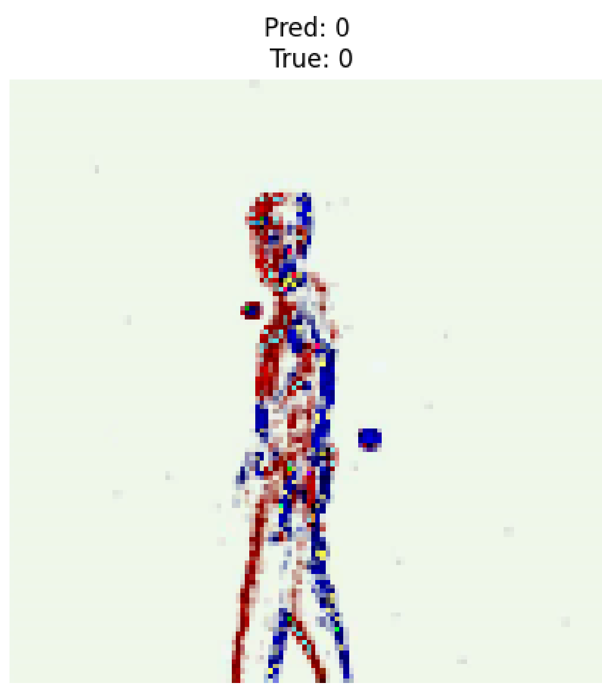

Fig. 2: An Example of a Successful Recognition of Walking Instance

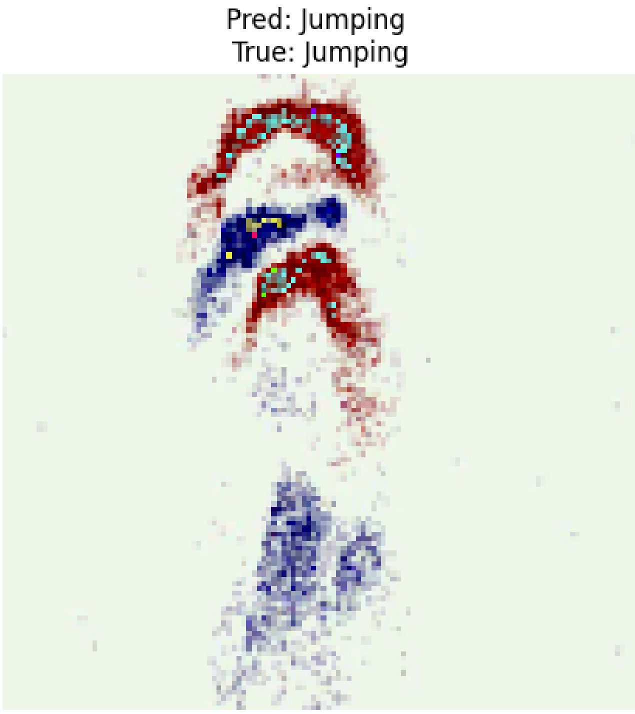

Fig. 3: An Example of a Successful Recognition of Jumping Instance

III. Results and Discussion

The Few-Shot Learning (FSL) framework demonstrated promising results, particularly in higher-shot scenarios, with observable trends in support and query accuracy:

- **Accuracy Trends:** Table I shows that increasing the number of support samples significantly improved query accuracy. In the 20-shot scenario, query accuracy reached 95% for the ”Jumping” activity, highlighting the model's capacity to generalize with ample support data. However, low-shot scenarios, such as the 5-shot ”Walking” task, resulted in 0% query accuracy, indicating poor performance due to limited training data. The model's performance is highly dependent on the quantity and quality of support data.
- **Prototypical Representations:** Prototypes captured distinct class-specific features, allowing the model to accurately classify activities such as ”Boxing,” ”Walking,” and ”Jumping.” The embedding space visualizations (Figures 1, 2, 3) illustrate how the model effectively separated these classes, particularly in high-shot settings.
- **Catastrophic Forgetting Mitigation:** The implemented strategies, including prototype preservation and embedding regularization, effectively mitigated catastrophic forgetting. The results indicated minimal accuracy degradation when new query tasks were introduced, suggesting strong scalability and robustness in handling incremental tasks.
- **Limitations:** The framework struggled with low-shot scenarios, such as the 5-shot ”Walking” task, which failed to generalize effectively. This limitation is attributed to insufficient class-specific information in smaller support sets. Future research could address this issue through data augmentation techniques, enhanced prototype adaptation, or hybrid architectures integrating attention mechanisms.

TABLE I: Few-Shot Classification Results (Accuracy %)

Scenario	Support Accuracy	Query Accuracy
5-shot Boxing query	56.15	20.00
5-shot Walking query	57.68	0.00
5-shot Jumping query	55.94	40.00
10-shot Jumping query	63.50	70.00
10-shot Boxing query	50.54	30.00
10-shot Walking query	52.29	50.00
20-shot Walking query	57.68	50.00
20-shot Jumping query	49.17	95.00
20-shot Boxing query	68.95	80.00

IV. Conclusion

In conclusion, our FSL framework effectively recognized human activities from neuromorphic data, even with limited labeled samples. Key takeaways include:

- Prototypical networks provide a robust foundation for FSL tasks, especially when combined with prototype preservation strategies.
- Mitigating catastrophic forgetting ensures the system's scalability to new tasks without compromising previously learned knowledge.
- Future work should focus on integrating attention mechanisms or transformers to enhance embedding representations further and support continual learning.

By combining these advancements, this study contributes to bridging the gap between neuromorphic sensing and practical real-time machine learning applications.

References

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