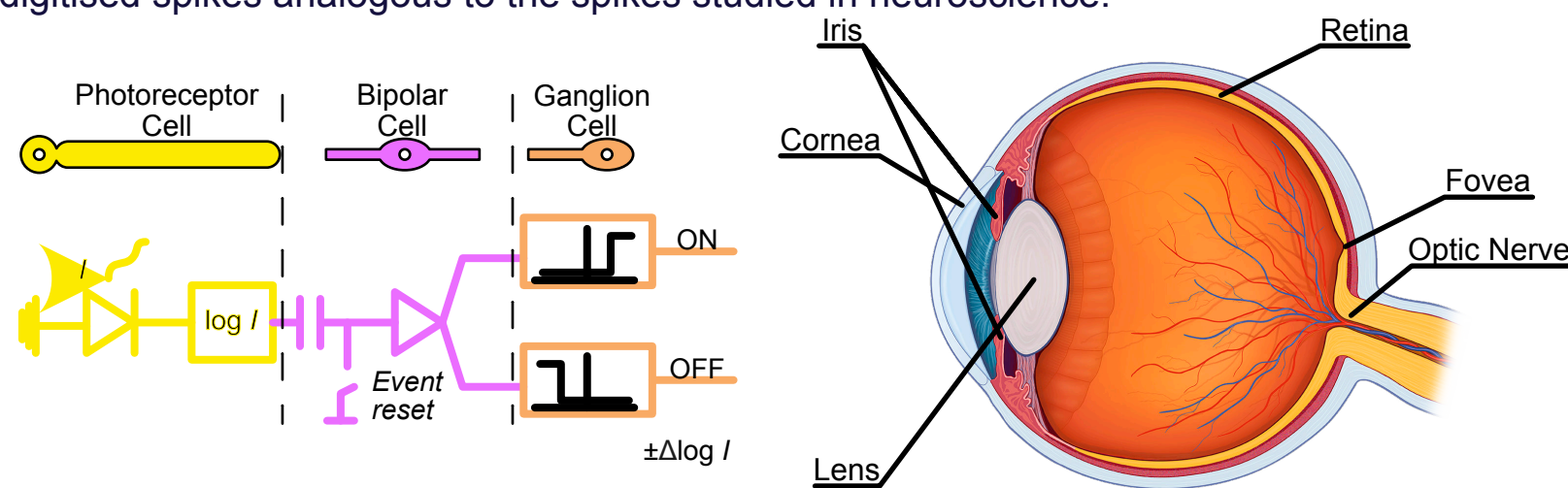


Introduction

A common practice in event-based vision is to project event data onto a 2D image plane such as a time-surface or surface-of-active-events which can be treated as a event-frame similar to a motion history image in frame-based vision. This allows for access to the rich and well-understood methods used in frame-based computer vision research but adds some unnecessary disadvantageous when coupled with event-based data namely quantisation of events, loss of speed and data sparsity. We present the reducing-over-time (ROT) tree for event-based data which does allows for the production of salient information without the 2D planar projection costs. The accuracy results of popular classification methods are shown to increase when ROT is applied as a noise filter.

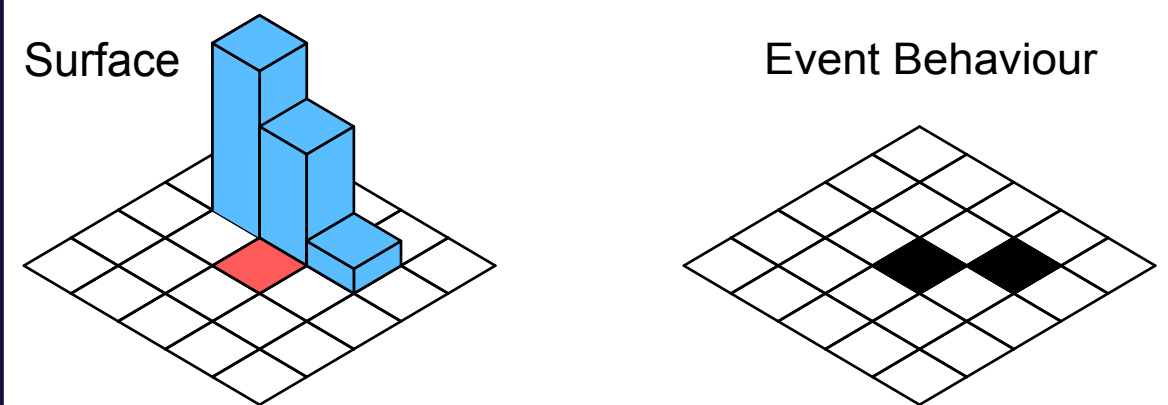
Event-based Vision

Event-based vision is a paradigm shifting approach to vision information capturing and representation which is bio-inspired. Event-based vision sensors typically emulate the retina neural behaviour when under stimuli, this approach per-pixel level produces asynchronous digitised spikes analogous to the spikes studied in neuroscience.

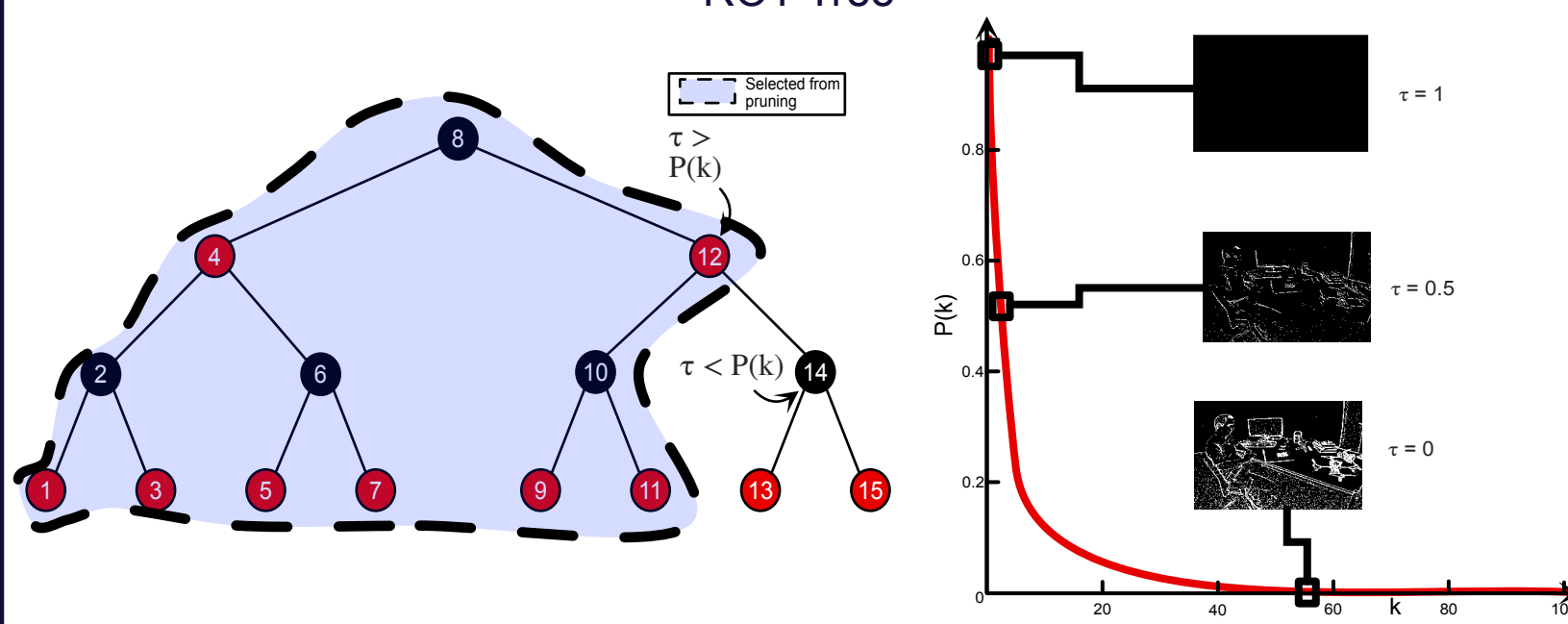


Event-based Projection

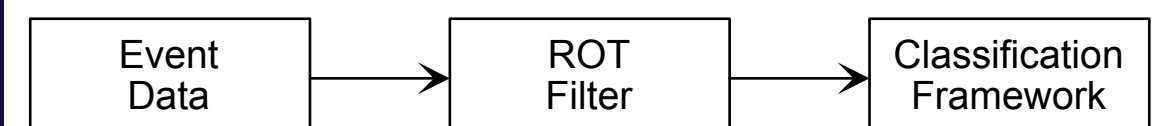
It is common in event-based vision to project data onto a 2D image plane, normally using integration of the data over time to produce event-frames; such as the time-surface and surface-of-active-events which can be analysed using classical frame-based techniques and allow for observation of event data behaviour over time.



ROT Tree



Setup



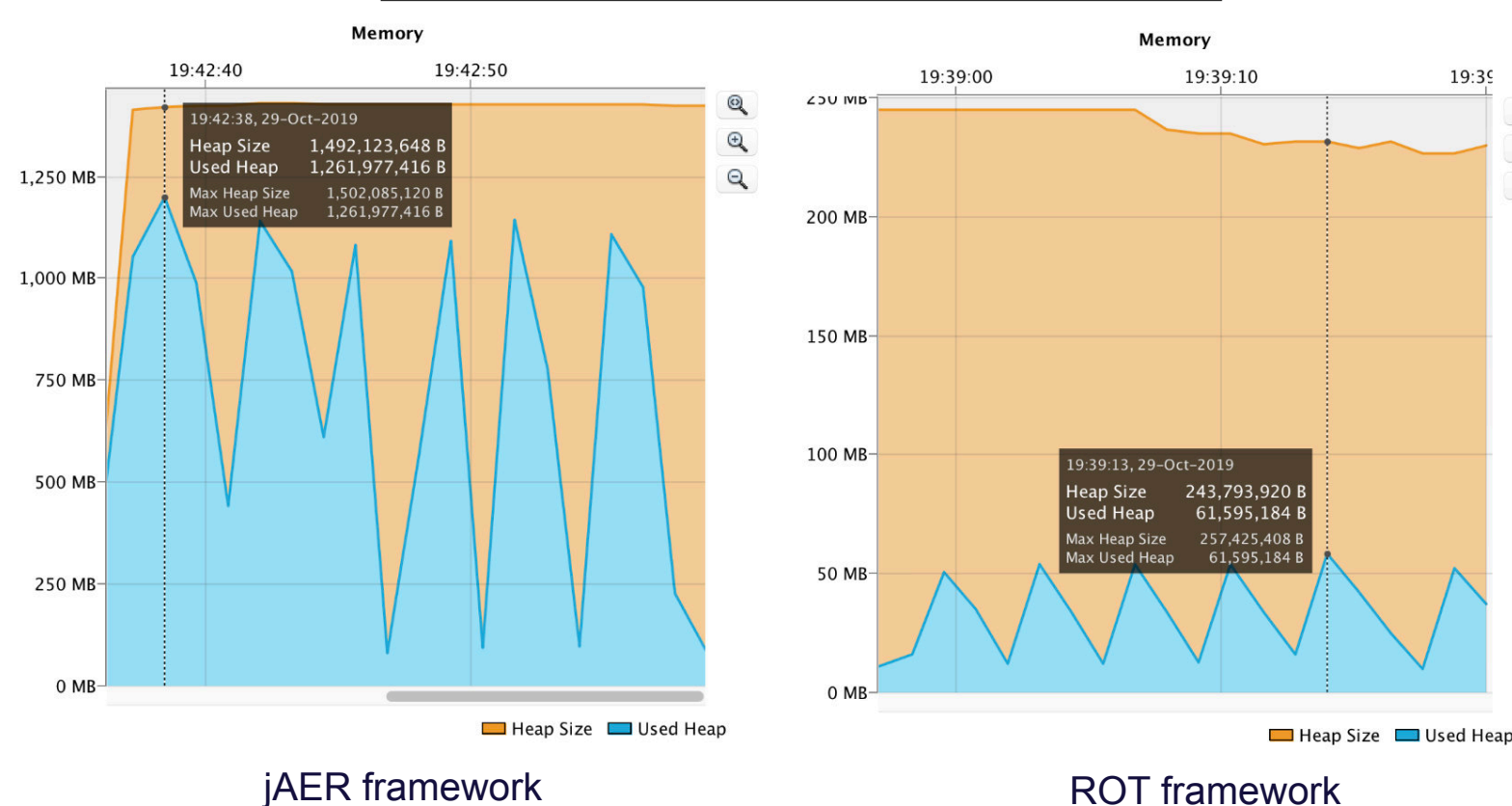
Results

We used the ROT as a filter of event-based data to reduce to salient points such as high probability edge events; the filter produced a rich-sparse data subset of the original input data. This subset was passed to popular objection recognition frameworks to observe if the subset increased the accuracy of the frameworks. We used the DART [1] and P-TED [2-3] frameworks.

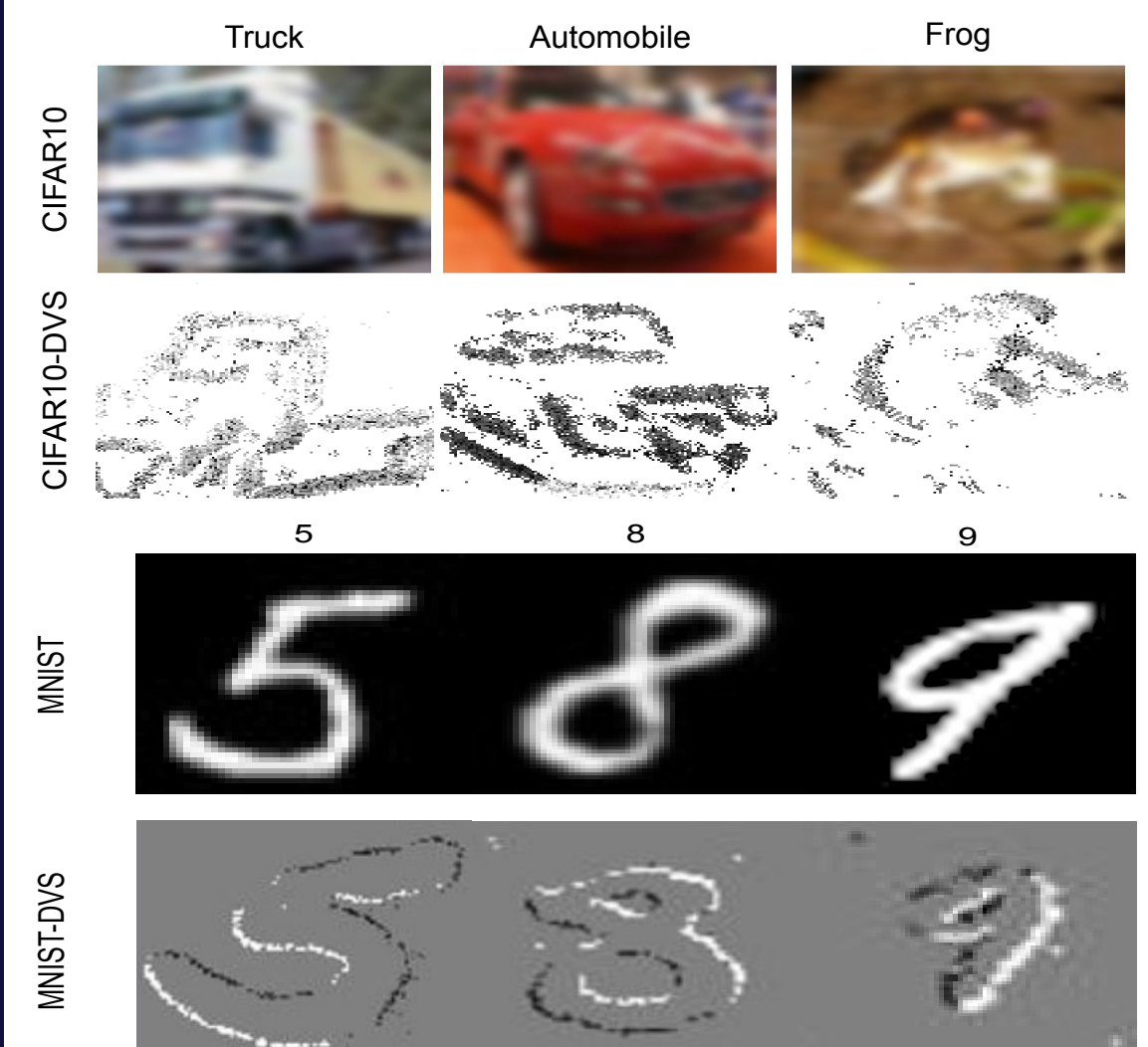
DATASET\FRAMEWORK	P-TED (%)	P-TED(ROT) (%)	DART (%)
<i>N-MNIST</i>	93.09	98.44	91.12
<i>MNIST-DVS</i>	91.73	96.71	86.74
<i>MNIST-FLAST-DVS</i>	94.80	96.93	93.20
<i>CIFAR10-DVS</i>	58.55	71.80	51.74

Additionally we analysed the memory usage of the framework in comparison to popular event-based data platforms which operate in over linked lists

Platform	Memory(Mb)
<i>cAER</i>	56
<i>ROT Framework</i>	62
<i>Tarsier, Sepia, Chameleon (TSC)</i>	81
<i>pyAER</i>	186
<i>python-aer</i>	196
<i>iAER</i>	1262



Dataset



Conclusion

This work presents a novel ROT tree for event-based data. This tree is self-balancing and self-pruning resulting in near-real time event data processing without the need to perform event projection onto an image plane; in particular we present initial methods for the acquisition of salient features (such as edges) within the event data and we use the salient features within popular classification frameworks. We found that using the ROT as a pre-filter for event-based data showed a desirable increase in classification accuracy while being memory efficient.

References

- [1] Ramesh, B., Yang, H., Orchard, G.M., Le Thi, N.A., Zhang, S. and Xiang, C., 2019. Dart: distribution aware retinal transform for event-based cameras. *IEEE transactions on pattern analysis and machine intelligence*.
- [2] Harrigan, S., Coleman, S., Kerr, D., Yogarajah, P., Fang, Z. and Wu, C., 2020, October. Post-Stimulus Time-Dependent Event Descriptor. In *2020 IEEE International Conference on Image Processing (ICIP)* (pp. 385-389). IEEE.
- [3] Harrigan, S., Coleman, S., Kerr, D., Yogarajah, P., Fang, Z. and Wu, C., 2020, May. Neural Coding Strategies for Event-Based Vision Data. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)* (pp. 2468-2472). IEEE.