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ROBOTICS & PERCEPTION GROUP

Unsupervised Feature Learning for Event Data: Direct vs Inverse Problem Formulation

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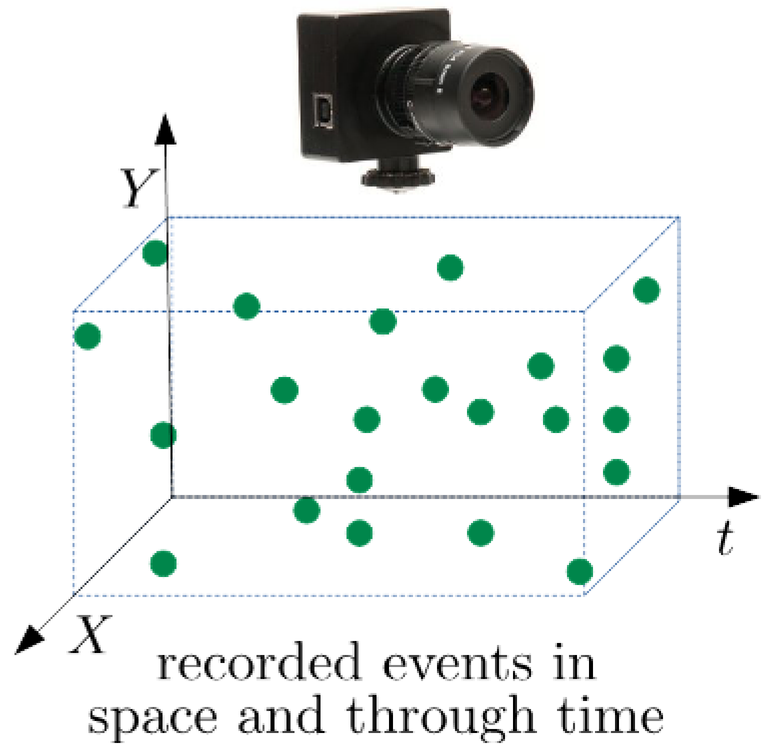
Introduction

- Event-based camera
  - Captures changes in intensity
  - Asynchronous
  - Advantages
    - High temporal resolution,
    - High dynamic range and
    - No motion blur



- Key question
  - How to extract meaningful and useful information?

Prior Work

- Handcrafted feature extraction approaches for event-based data

- Learning based approaches for event-based data
  - Spiking Neural Networks (SNNs) [21] for event-based camera
  - Standard Neural Networks [5], [11], [4], [3] for event-based camera

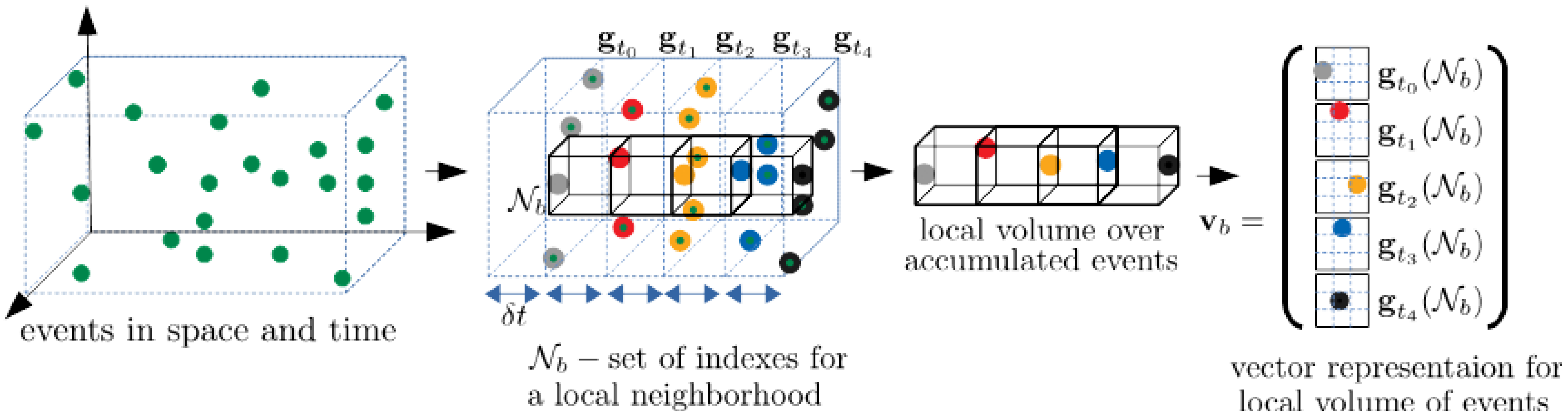
- Applications
  - Gesture recognition [22],
  - Object recognition [27], [4],
  - Face detection [7],
  - Optical flow prediction [37], [34] and
  - Image reconstruction [26]

Motivation

- Data-adaptive, learned single-layer architectures for event-based data not studied extensively
- Unknown to which extend a single-layer model could be useful for event-based data and
- How the spatial and temporal resolution of the event-based data impacts performance for a recognition task

Unsupervised Feature Learning

- Local volume of events extraction

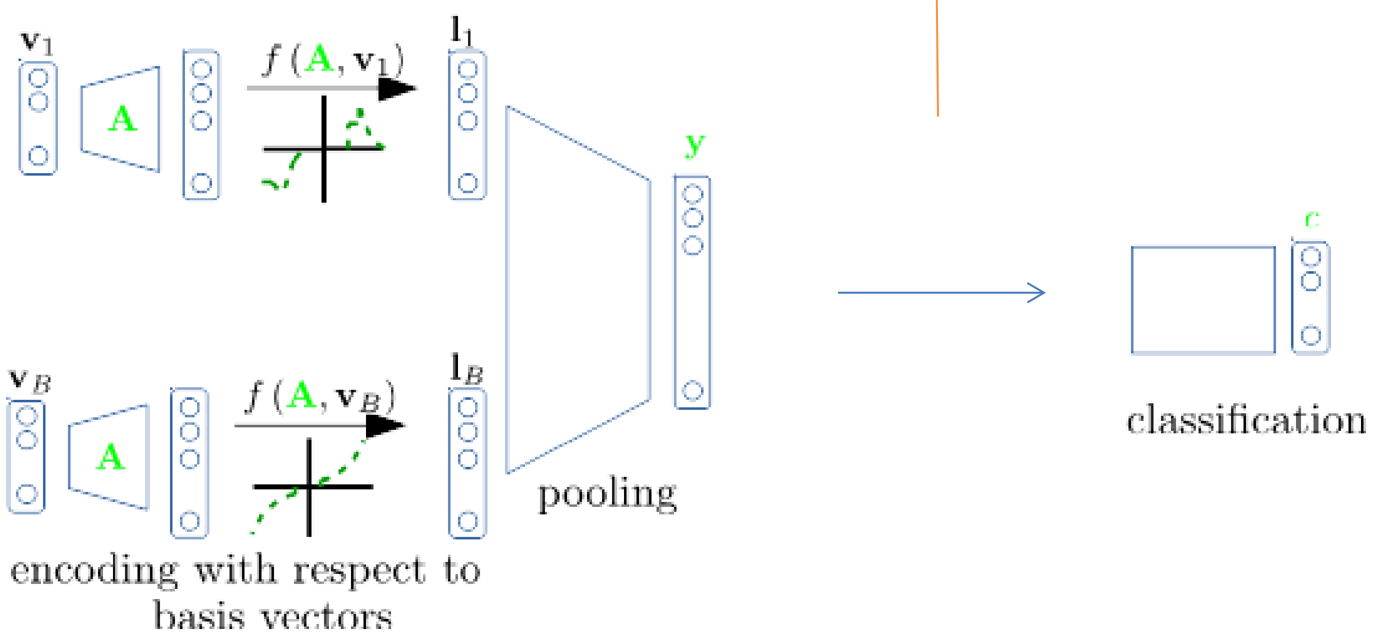


Unsupervised Feature Learning

- Two part recognition pipeline

Part one: unsupervised feature learning + pooling
(learning a mapping with basis vectors as parameters)
-Direct problem formulation
-Inverse problem formulation

Part two: Classifier learning
-Linear SVM



Numerical Evaluation

- Data sets
  - N-MNIST (10 digits, around 1000 samples per digit)
  - N-CARS (foreground/background, around 10000 per class)
  - N-Caltech101 (101 objects, dis-balanced number of samples per object)
- Learned unsupervised feature mapping as proposed using
  - Direct and
  - Inverse problem formulation
- Classifier
  - Linear SVM
- Used quantitative measures
  - Acc. (measured as average of the classifier prediction accuracy over the test set)

Numerical Evaluation

- Accuracy on all of the data sets

Data set	Acc. % (inverse)	Acc. % (direct)
N-MNIST	98.1	96.8
N-Calteh101	78.4	77.1
N-CARS	84.7	81.3

- Comparison with state-of-the-art on the Caltech101 dataset

Method	Acc. %
Hfist [14]	06.0
HOTS [2]	21.0
Garbor-SNN [41]	19.2
HATS [4]	64.2
DART [30]	70.3

Method	Acc. %
Proposed (inverse)	**78.4**
Proposed (direct)	**77.1**

single-layer architectures

Method	Acc. %
EST [16]	81.7
VID2E [10]	90.1

multi-layer architectures

Numerical Evaluation

- Accuracy under varying: number of basis vectors, size of the local volume and number of accumulation intervals

Method	Number of Basis Vectors			
	1000	1500	1700	2000
Proposed (inverse)	73.2	74.5	78.4	76.0
Proposed (direct)	74.3	77.0	77.1	75.5

Method	Size of the Local Volume			
	4×4×4	4×12×12	4×16×16	4×21× 21
Proposed (inverse)	69.6	78.4	76.4	75.2
Proposed (direct)	64.8	77.1	74.5	75.1

Method	Number of Accumulation Intervals			
	2	4	7	10
Proposed (inverse)	61.7	72.4	78.4	76.3
Proposed (direct)	63.2	69.1	77.1	74.1

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