Telluride 2018 Neuromorphic Cognition Engineering Workshop

July 1-20, 2018. Telluride, Colorado, USA

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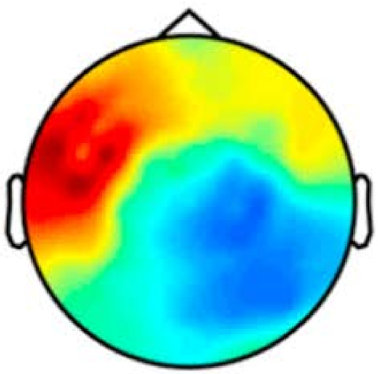
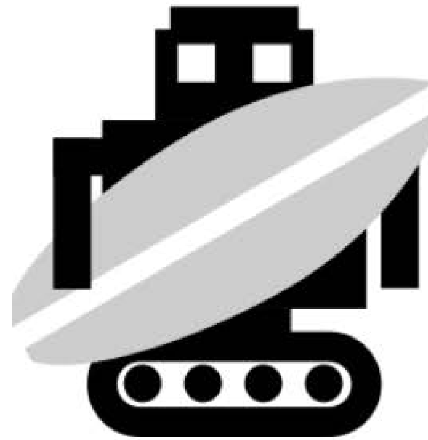
Topic Areas

AUD18: Prediction and Surprise in Natural Sound Processing: Comparing DNNs to the human brain

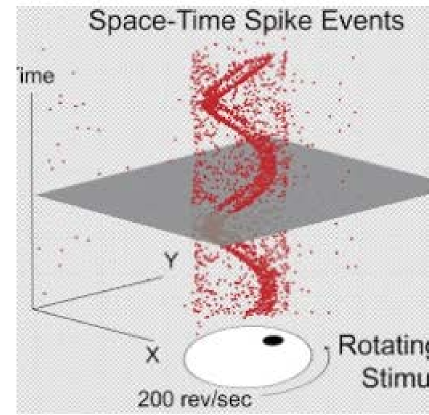


BRD18: Building applications with Braindrop —a novel neuromorphic chip for embodied perception and action

CAL18: Cognitive Agents that Learn in the Wild



ESP18: Fundamentals of Event Sensor Signal Processing



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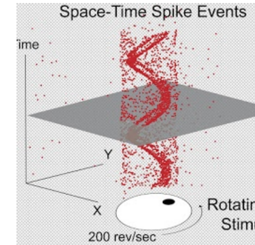
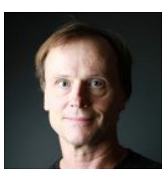


ESP18: Fundamentals of Event Senor Signal Processing

- 1 . Can we lay a practical mathematical foundation that allows deriving efficient event-driven signal processing algorithms, analogous to the Z-**transform** of DSP?
- 2. Can we find better **noise reduction (NR)** algorithms than existing ones?
- 3. Can we find general methods for **adaptively controlling sensor parameters** like threshold, bandwidth, and refractory period?
- 4. Can we find **better input representations** for event cameras data for CNN?
- 5. What can we do to combine DVS events with **color vision**?



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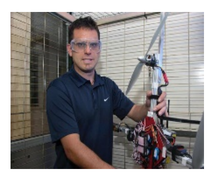

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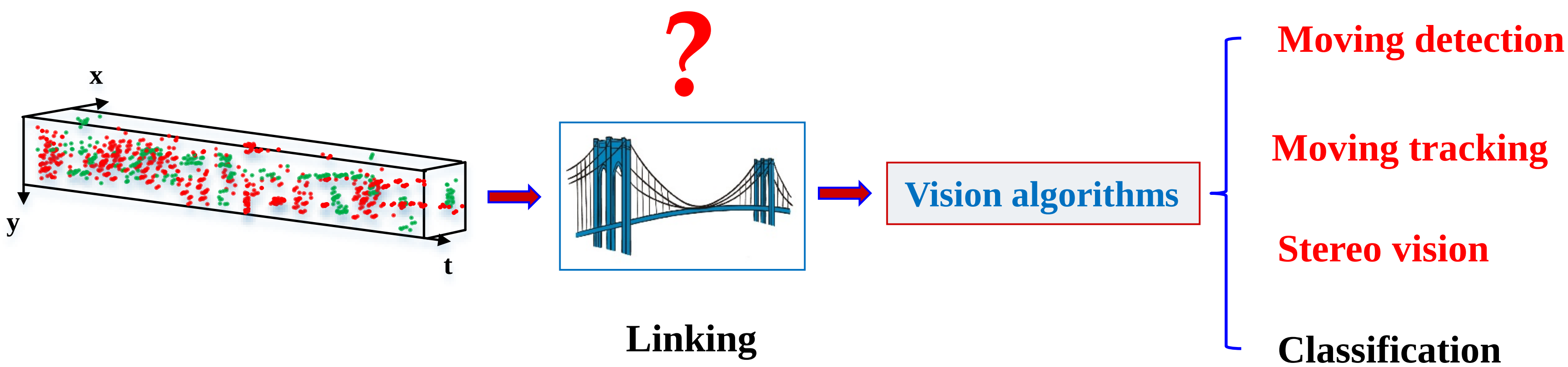
How to find better input representations for event-based camera data?

Jianing Li Spiking Computing Group lijianing@pku.edu.cn

Sep. 28, 2018

Motivation

- **Sparse and asynchronous spatial-temporal events**
  - High temporal resolution
  - Low spatial resolution



Overview

- **Introduction**
  - Event-based sensors
  - Related works
- **Image representations**
  - Steering prediction, CVPR 2018
- **Time surface representations**
  - HOTS, PAMI 2017
  - HATS, CVPR 2018
- **Feature representations**
  - Bag of Events, TNNLS 2017
- **End-to-end SNN**
  - STDP, TNNLS 2014
- **Discussion**
  - Better input representations for CNN
  - Event-based sensors future

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Event-based sensors

Milestones

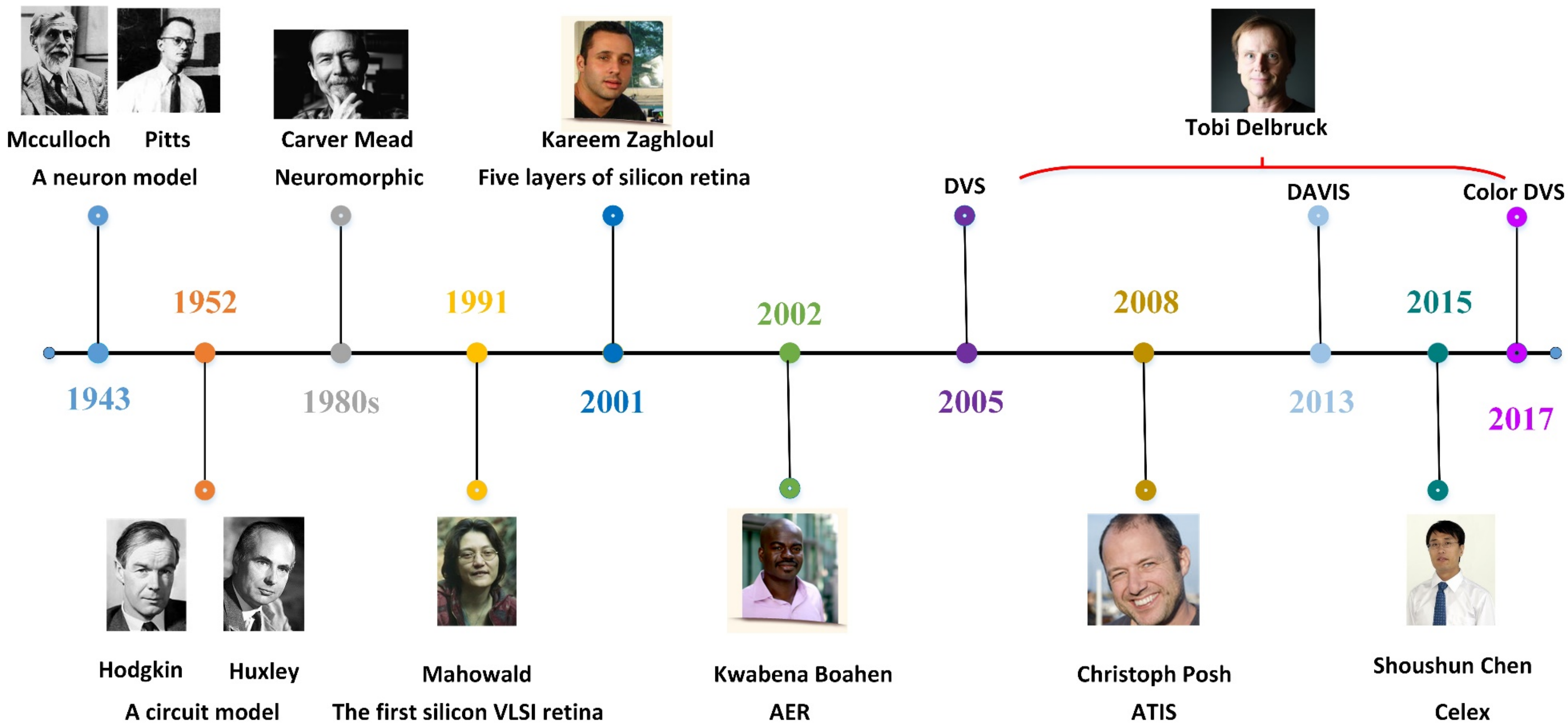


Fig.1 The time diagram for vision devices [1]

[1] Retinomorphic Event-Based Vision Sensors: Bioinspired Cameras With Spiking Output, C Posch. *Proceedings of IEEE*, 2014.

Event-based sensors

Bioinspired vision

The advantage

(1) High temporal resolution
(2) Low redundancy
(3) High dynamic range

The disadvantage

(1) Sensitive to noise
(2) Low spatial resolution
(3) Spatio-temporal sparse

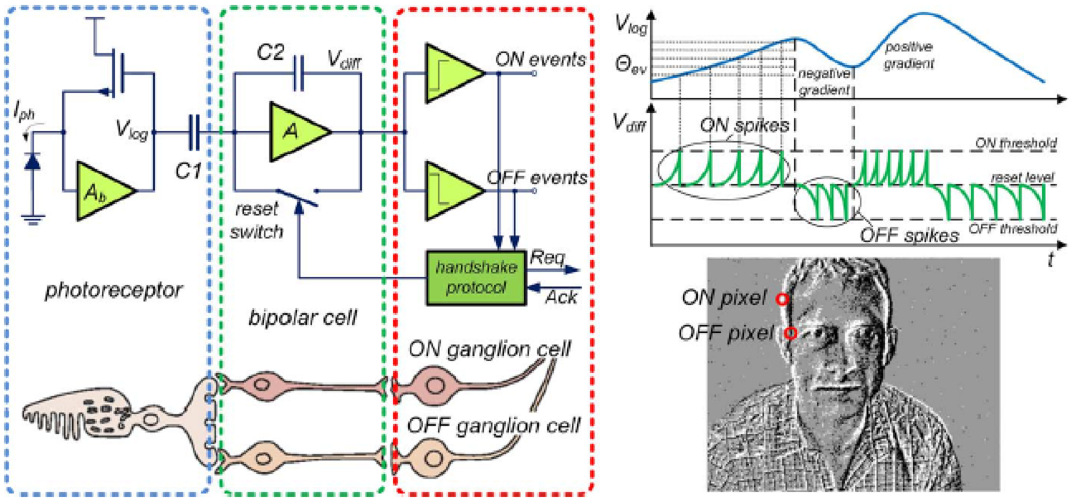


Fig.2 Three-layer model of silicon retina and DVS [1]

$$ev_i = [X_i, t_i, p_i]^T, i \in N$$

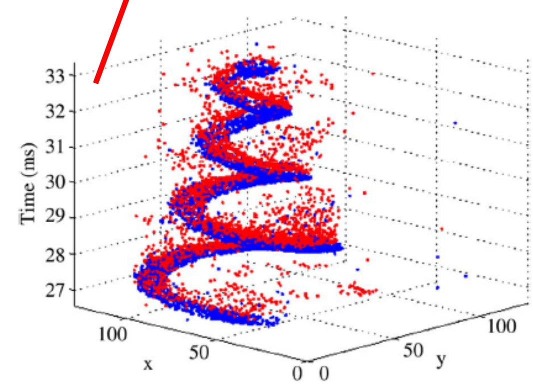


Fig.3 Illustration of DVS output [1]

[1] Retinomorphic Event-Based Vision Sensors: Bioinspired Cameras With Spiking Output, C Posch. *Proceedings of IEEE*, 2014.

Event-based sensors

Cameras

Camera	DVS	ATIS	DAVIS	Celex
Function	Dynamic event	Dynamic event + Intensity	Dynamic event + image capture	Dynamic event + image capture
First release year	2005	2008	2013	2017
Fixed Pattern noise	2.1%	0.25% intensity	0.5%APS, DVS 3.5%	0.38%
Power consumption	24mW	175mW (high activity) 50mW(low activity)	14mW(high activity) 5mW(low activity)	700mW
Array size	128*128	304*240	240*180	**1280*720**
Pixel Size(um^2)	40*40	30*30	18.5*18.5	30*30
Latency	15us@1klux	4us@1klux	3us@1klux	6us@1klux
Dynamic range	**120dB**	**125dB**	**130dB DVS** **51dB APS**	**120dB**
Commercialization	Commercialized (DVS128)	Commercialized (ATIS304)	Commercialized (DAVIS240)	Prepared

Tab.1 Papers of event-based vision in related topics [2,3]

[2] A Review of Bioinspired Vision Sensors and Their Applications, D Cho et al. ***Sensors & Materials*** , 2015.
[3] A Dynamic vision with direct logarithmic output and full-frame picture-on-demand, M Guo. ***PHD***, 2016.

Event-based sensors

☐ DVS VS standard camera

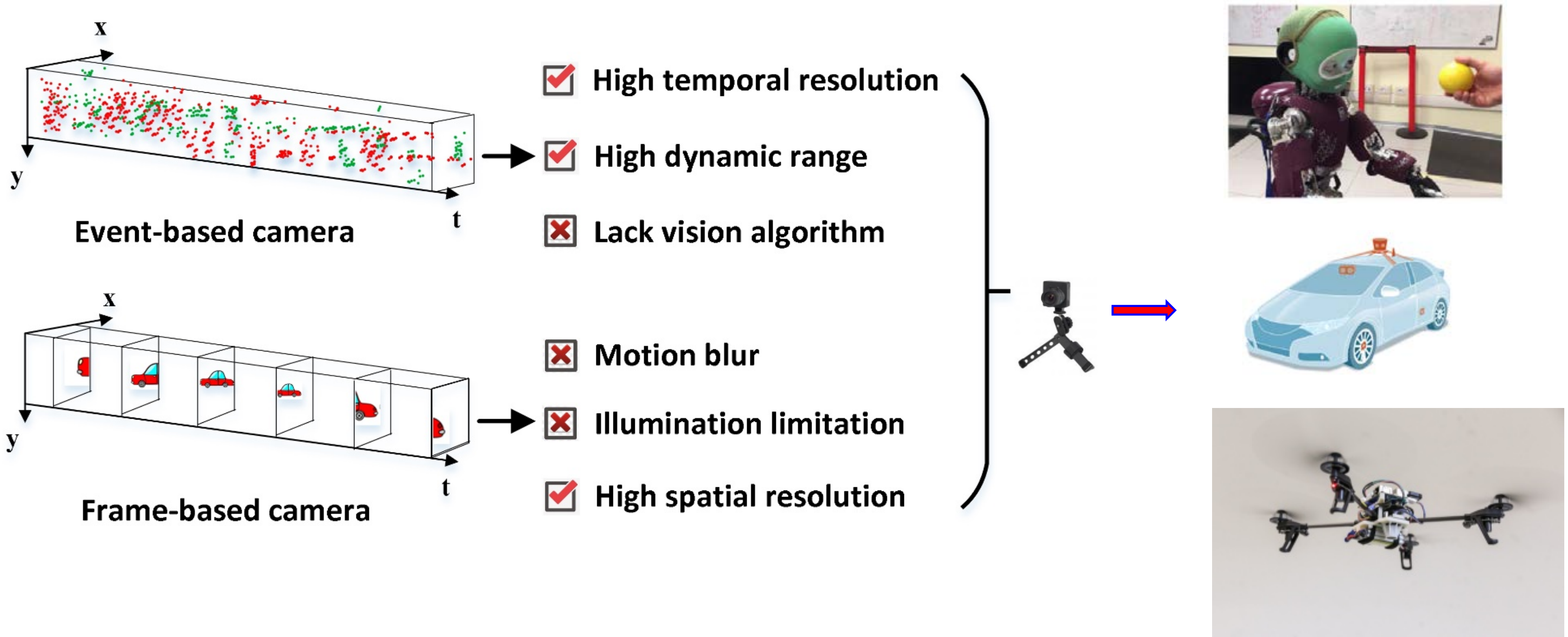


Fig.4 Event-based and frame-based cameras in applications

Event-based sensors

- **Embedded neuromorphic chip**
  - To mimic neural network architecture of biological brains
  - Low-power

TureNorth [4]
IBM

SpiNNaker [5]
Uni. Manchester

Loihi [6]
Intel

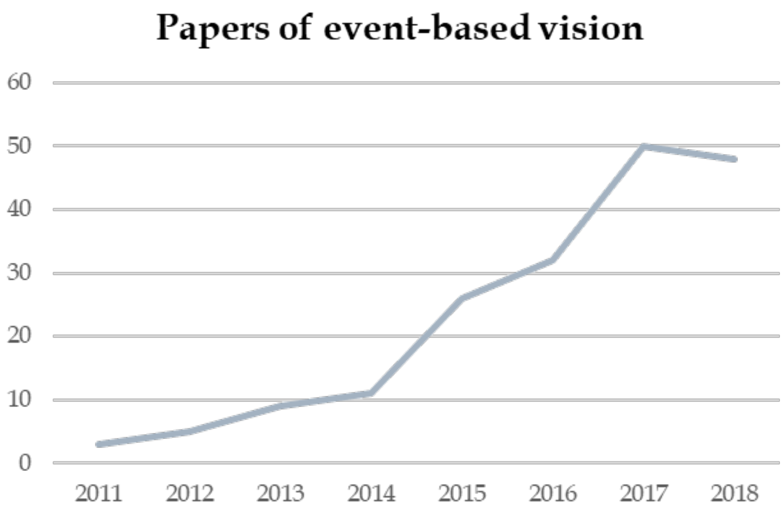
Fig.5 Bioinspired neuromorphic chips

[4] A million spiking-neuron integrated circuit with a scalable communication network and interface, Paul A. Merolla et.al, ***Science***, 2014.
[5] The SpiNNaker Project, Steve B. Furber et.al, ***The Proceedings of IEEE***, 2014.
[6] Loihi: A neuromorphic manycore processor with on-chip learning, Mike Davies, ***IEEE micro***, 2018.

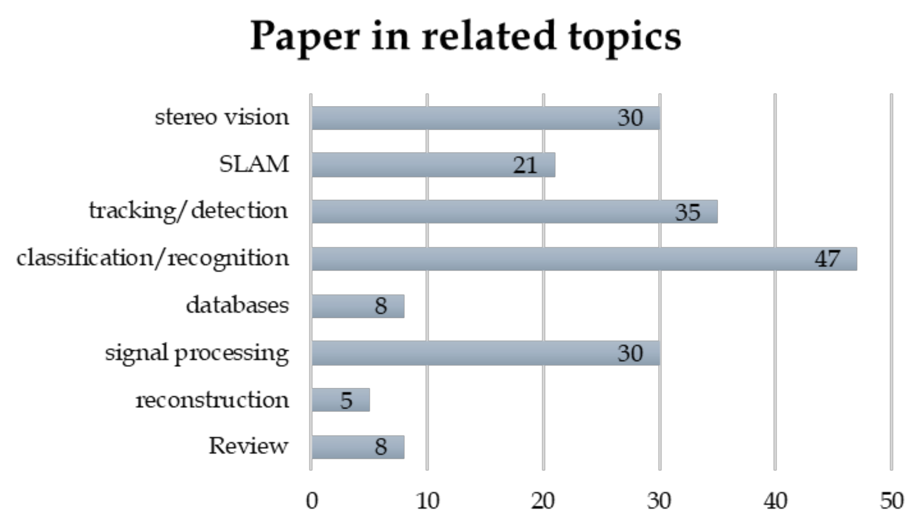
Related works

Event-based vision

- Research papers in recent years
- Related topics, mainly in vision applications



Tab.2 Papers of event-based vision in recent years



Tab.3 Papers of event-based vision in related topics

Tips: all statistical papers mainly are about DVS, ATIS and DAVIS.

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Event-based vision meet deep learning on steering prediction for self-driving cars

Ana I. Maqueda, Antonio Loquercio, Guillermo Gallego, Narciso Garcia,
Davide Scaramuzza *

CVPR, 2018

1 Introduction

Motivation

- Challenging illumination conditions
- Fast motion

Contributions

- **Deep learning to event-based vison on regression task**
- Show that possible transfer learning from pre-trained CNN
- Outperforming state-of-art systems

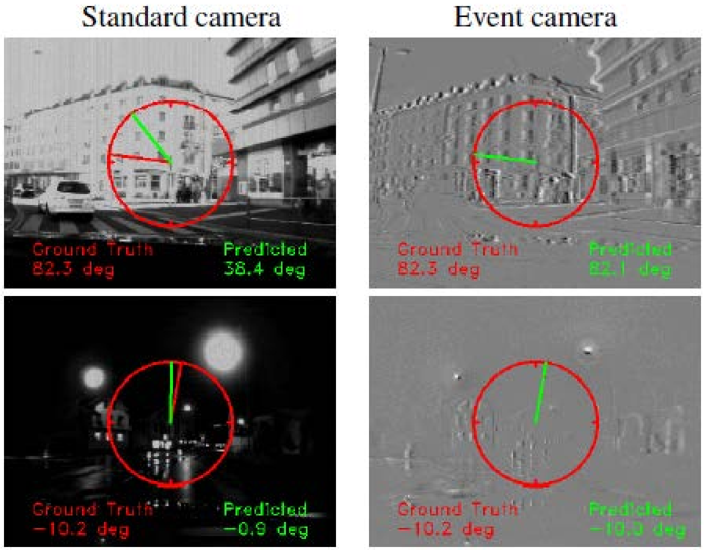

Fig.1 Steering angle performance on frames and event camera.

2 Framework

Methodology

- **Event-to-Frame conversation**
- Network architecture

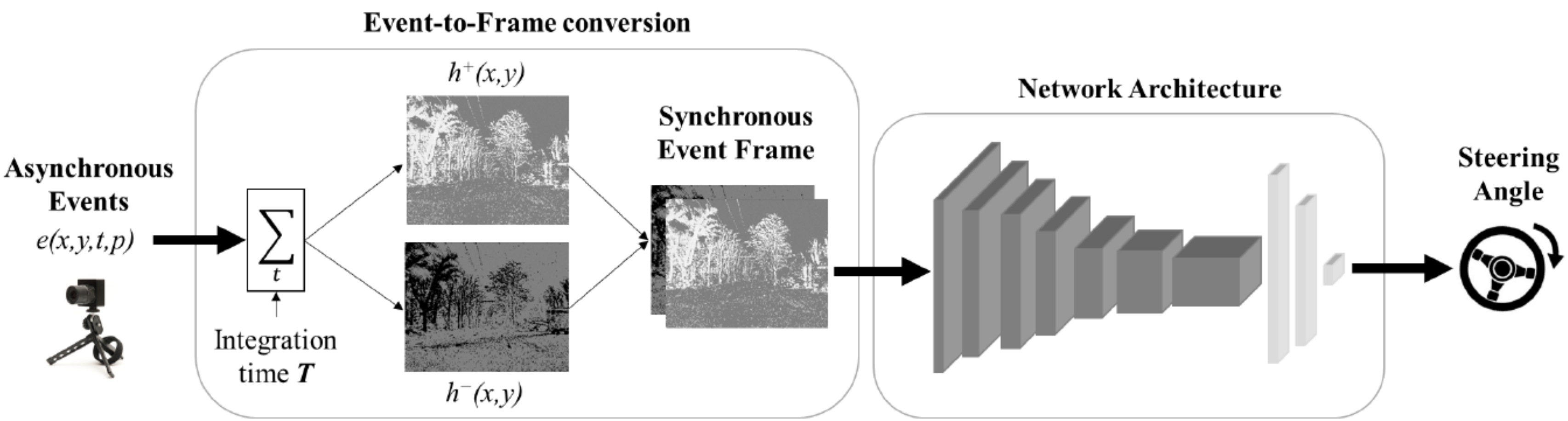

Fig.2 The framework of steering angle prediction based on event-based camera.

3 Integration time for events

Performance metrics

- RMSE
- EVA

$$\mathrm{RMSE} \doteq \sqrt{\frac{1}{N}\sum_{j=1}^{N}(\hat{\alpha}_j-\alpha_j)^2}.$$

$$\mathrm{EVA} \doteq 1-\frac{\mathrm{Var}(\hat{\alpha}-\alpha)}{\mathrm{Var}(\alpha)}.$$

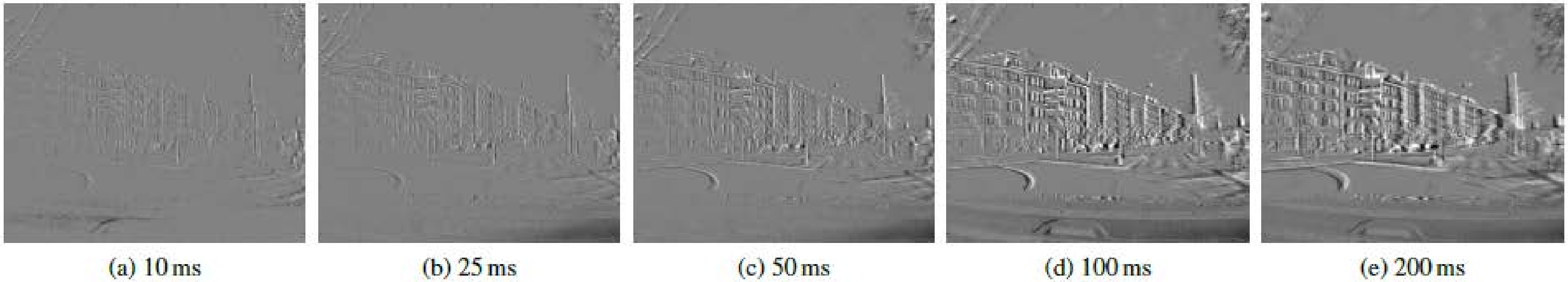

Fig.3 Events collected for different durations of the interval.

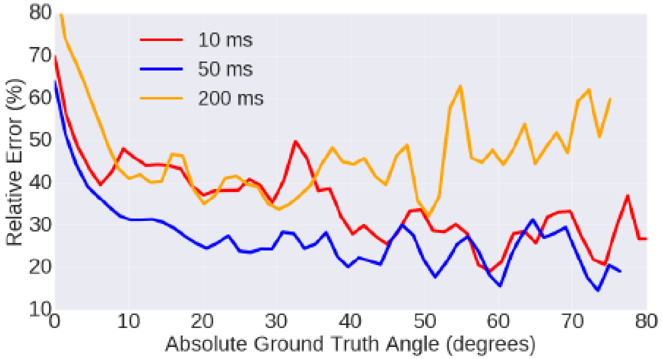

Fig.4 The relative error in steering angle prediction

Integration time T	EVA	RMSE
10 ms	0.790	11.53°
25 ms	0.792	10.42°
50 ms	**0.805**	**9.47°**
100 ms	0.634	13.43°
200 ms	0.457	15.87°

Tab.1 Comparison performances for different integration times

4 Experiments

Datasets

- DDD17 [1]

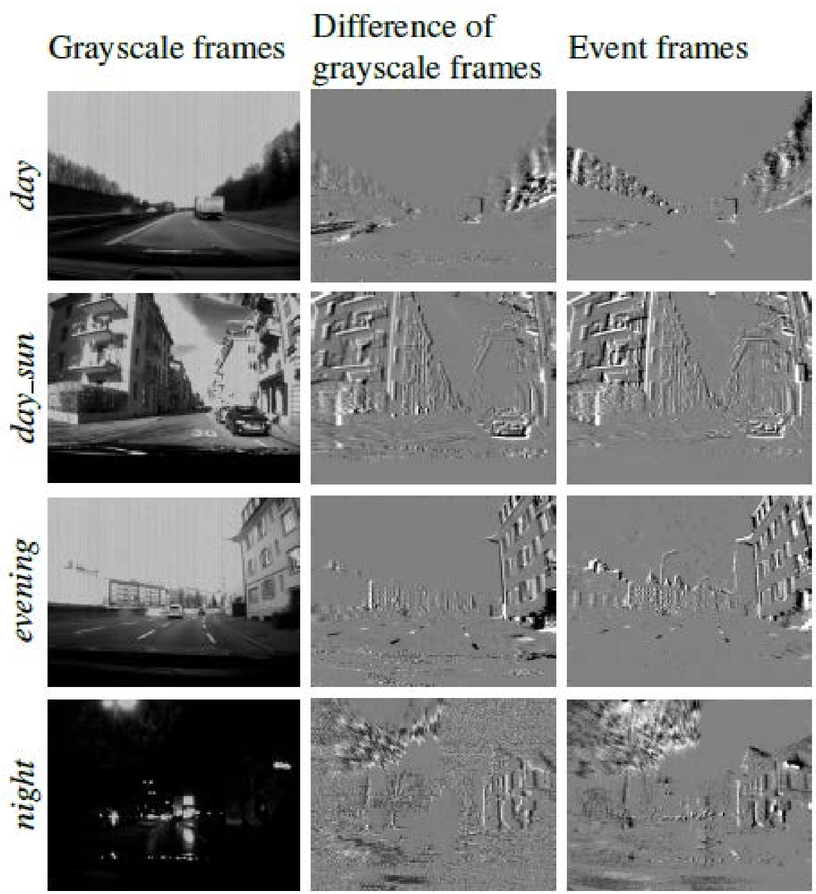

Fig.5 DDD17 dataset for four lighting conditions

Architecture	Grayscale EVA	Grayscale RMSE	Grayscale diff. EVA	Grayscale diff. RMSE	Events EVA	Events RMSE
ResNet18	0.047	4.57°	0.329	3.65°	**0.551**	**2.99°**
ResNet50	0.449	3.31°	0.653	2.62°	**0.728**	**2.33°**

Tab.2 Results for day subset

Architecture	Grayscale EVA	Grayscale RMSE	Grayscale diff. EVA	Grayscale diff. RMSE	Events EVA	Events RMSE
ResNet18	0.125	20.07°	0.729	11.53°	**0.742**	**10.87°**
ResNet50	0.383	16.85°	0.802	9.62°	**0.805**	**9.47°**

Tab.3 Results for day_sun subset

Architecture	Grayscale EVA	Grayscale RMSE	Grayscale diff. EVA	Grayscale diff. RMSE	Events EVA	Events RMSE
ResNet18	0.172	7.23°	0.183	7.19°	**0.518**	**5.45°**
ResNet50	0.360	6.37°	0.418	6.07°	**0.602**	**5.01°**

Tab.4 Results for evening subset

Architecture	Grayscale EVA	Grayscale RMSE	Grayscale diff. EVA	Grayscale diff. RMSE	Events EVA	Events RMSE
ResNet18	0.181	6.96°	0.449	5.73°	**0.654**	**4.51°**
ResNet50	0.418	5.88°	0.621	4.73°	**0.753**	**3.82°**

Tab.5 Results for night subset

[1] DDD17: End-to-end DAVIS driving dataset, Jonathan Binas et.al. ***ICML workshops***, 2017.

5 Outlook

- **1** **Adaptive integration time** to convert into images?
- **2** Generating feature maps based on **SNN**?
- **3** **Joint** frame-based and event-based in predicting steering angle?
- **4** How to use high temporal information?

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HATS: histograms of averaged time surfaces for robust event-based object classification [1]

Amos Sironi, Manuele Brambilla, Nicolas Bourdis, Xavier Lagorce, **Ryad B. Benosman ***

CVPR, 2018

[1] HOTS: A hierarchy of event-based time-surfaces for pattern recognition. Xavier Lagorce et.al . *PAMI* 2017.

1 Related works

Time surface

- Event streams

$$ev_i = [\mathbf{x_i}, t_i, p_i]^T, \quad i \in \mathbb{N}$$

- Time context

$$\mathcal{T}_i(\mathbf{u}, p) = \max_{j \leq i}\{t_j \,|\, \mathbf{x_j} = (\mathbf{x_i} + \mathbf{u}),\, p_j = p\}$$

- Computing time surface

$$\mathcal{S}_i(\mathbf{u}, p) = e^{-(t_i - \mathcal{T}_i(\mathbf{u}, p))/\tau}.$$

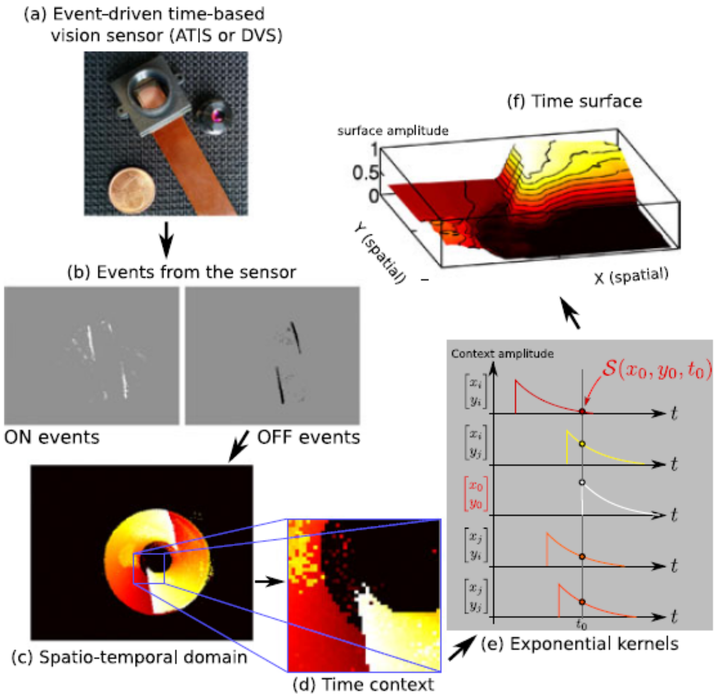

Fig.1 Time surface from the spatiotemporal events

1 Related works

- **Feature representations**
  - Online clustering of time-surfaces
  - Extracting features

$$feat_i = [x_i, y_i, t_i, k_i]^T,$$

Algorithm 1. Online Clustering of Time-Surfaces

Ensure: N cluster centers $\mathbf{C}_n$, $n \in [\![1, N]\!]$
  Use the first N events' time-surfaces as initial values for $\mathbf{C}_n$, $n \in [\![1, N]\!]$
  Initialize $p_n \leftarrow 1$, $n \in [\![1, N]\!]$
  for every incoming event ev_i **do**
    Compute time-surface $\mathcal{S}_i$
    Find closest cluster center $\mathbf{C}_k$
    $\alpha \leftarrow 0.01/(1 + p_k/20000)$
    $\beta \leftarrow \mathbf{C}_k \cdot \mathcal{S}_i/(||\mathbf{C}_k|| \cdot ||\mathcal{S}_i||)$
    $\mathbf{C}_k \leftarrow \mathbf{C}_k + \alpha(\mathcal{S} - \beta\mathbf{C}_k)$
    $p_k \leftarrow p_k + 1$
  end for

Tab.1 Online clustering of event streams based on time-surfaces

1 Related works

Framework

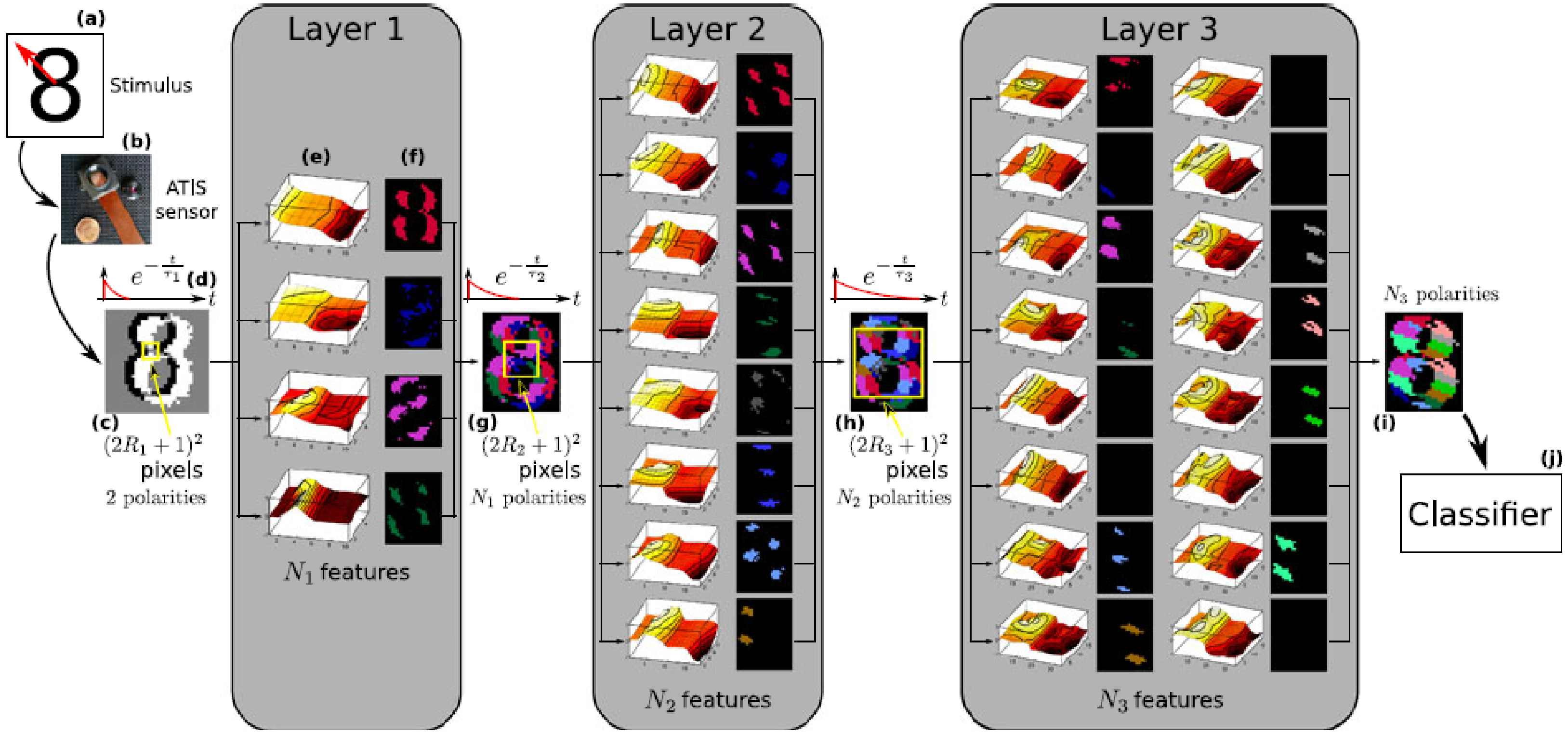

Fig.2 The proposed hierarchical framework based on time-surfaces

2 Introduction

- **Motivation**
  - Overcoming noisy events
  - Real-world event-based dataset
- **Contribution**
  - Local memory time surfaces
  - HATS—Histograms of averaged time surfaces
  - N-CARS dataset

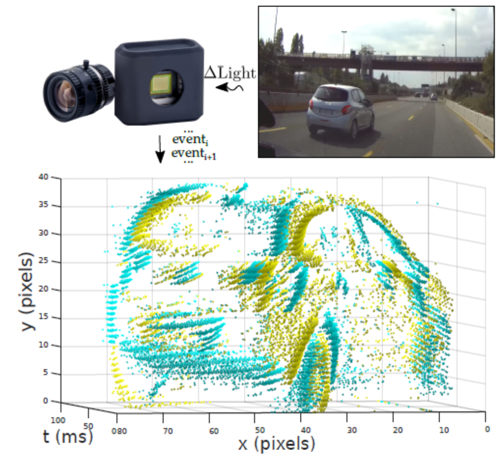

Fig.3 N-CARS dataset

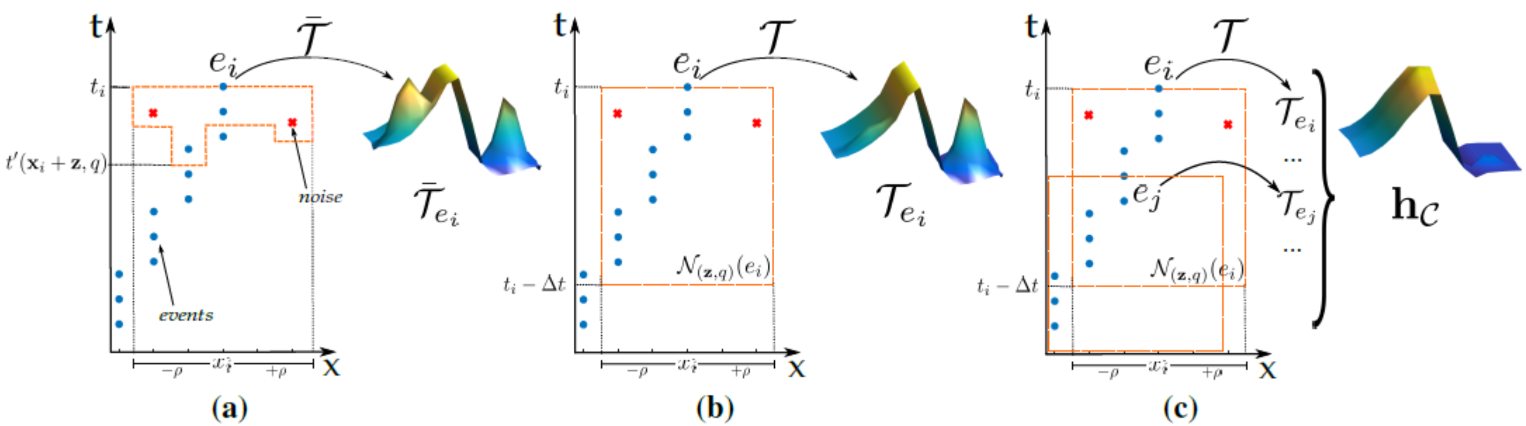

Fig.4 Time surface computation around an event, in presence of noise. (a)time surfaces; (b)local memory time surfaces; (c)HATS

3 Method

- **Local memory time surfaces**
  - Temporal window Δt

$$\mathcal{T}_{e_i}(\mathbf{z},q)=\begin{cases}\sum_{e_j\in\mathcal{N}_{(\mathbf{z},q)}(e_i)} e^{-\frac{t_i-t_j}{\tau}} & \text{if } p_i=q\\ 0 & \text{otherwise,}\end{cases}$$

$$\mathcal{N}_{(\mathbf{z},q)}(e_i)=\{e_j:\mathbf{x}_j=\mathbf{x}_i+\mathbf{z},t_j\in[t_i-\Delta t,t_i),p_j=q\}$$

- **Histograms of averaged time surfaces**
  - Averaged histogram

$$\mathbf{h}_{\mathcal{C}}(\mathbf{z},p)=\frac{1}{|\mathcal{C}|}\bar{\mathbf{h}}_{\mathcal{C}}(\mathbf{z},p)=\frac{1}{|\mathcal{C}|}\sum_{e_i\in\mathcal{C}}\mathcal{T}_{e_i}(\mathbf{z},p)$$

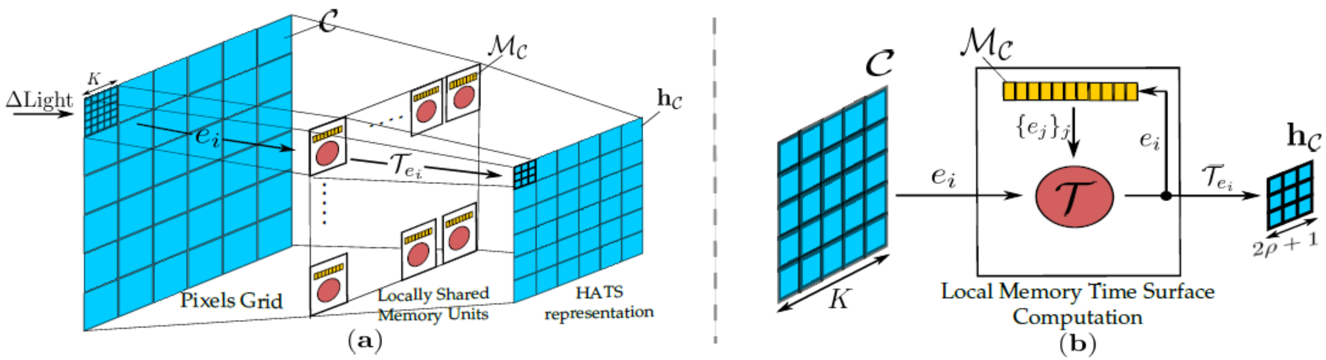

Fig.5 Overview of the proposed architecture. (a)Cells C; (b)Local memory time surface computation

3 Method

Algorithm

Algorithm 1 *HATS* with shared memory units

Input: Events $\mathcal{E} = \{e_i\}_{i=1}^{I}$ Parameters: $\rho, \Delta t, \tau, K$

Output: *HATS* representation $\mathbf{H}(\{e_i\})$

Initialize: $\mathbf{h}_{\mathcal{C}_l} = \mathbf{0},\ |\mathcal{C}_l| = 0,\ \mathcal{M}_{\mathcal{C}_l} = \emptyset$, for all l

for $i = 1, \ldots, I$ **do**

    $\mathcal{C}_l \leftarrow \mathrm{getCell}(x_i, y_i)$

    $\mathcal{T}_{e_i} \leftarrow \mathrm{computeTimeSurface}(e_i, \mathcal{M}_{\mathcal{C}_l})$

    $\mathbf{h}_{\mathcal{C}_l} \leftarrow \mathbf{h}_{\mathcal{C}_l} + \mathcal{T}_{e_i}$

    $\mathcal{M}_{\mathcal{C}_l} \leftarrow \mathcal{M}_{\mathcal{C}_l} \cup e_i$

    $|\mathcal{C}_l| \leftarrow |\mathcal{C}_l| + 1$

return $\mathbf{H} = [\mathbf{h}_{\mathcal{C}_1}/|\mathcal{C}_1|, \ldots, \mathbf{h}_{\mathcal{C}_L}/|\mathcal{C}_L|]^\intercal$

Tab.2 The algorithm of histograms average time-surfaces

4 Experiments

Classification accuracies

- database

Table 1 Compared methods for database

	N-MNIST	**N-Caltech101**	**MNIST-DVS**	**CIFAR10-DVS**
H-First [50]	0.712	0.054	0.595	0.077
HOTS [30]	0.808	0.210	0.803	0.271
Gabor-SNN	0.837	0.196	0.824	0.245
HATS (this work)	**0.991**	**0.642**	**0.984**	**0.524**
Phased LSTM [46]	0.973	-	-	-
Deep SNN [33]	0.987	-	-	-

Complexity analysis

- N-CARS

Table 2 Complexity analysis for N-CARS

N-CARS	Average Comp. Time per Sample (ms)	Kev/s
HOTS [30]	157.57	25.68
Gabor-SNN	285.95	14.15
HATS (this work)	**7.28**	**555.74**

5 Outlook

- **1** Decreasing **complexity**, rather than based on single spike?
- **2** **Local feature** representations?
- **3** **End-to-end architecture** used in spatial-temporal spike stream?

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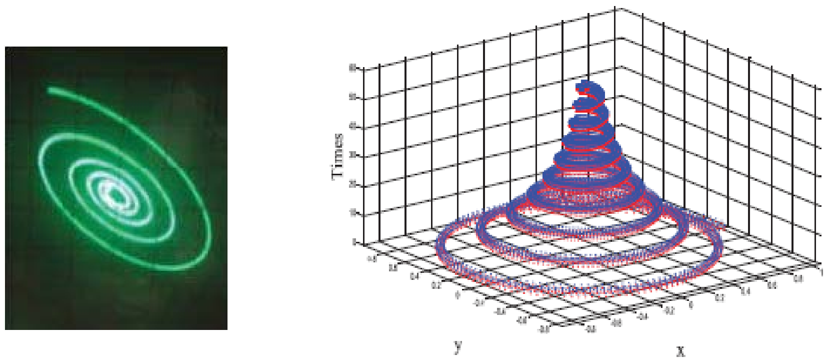
Bag of events: an efficient probability-based feature extraction method for AER image sensors

Xi Peng, Bo Zhao, Rui Yan, **Huajin Tang ***, Zhang Yi

TNNLS, 2017

1 Introduction

- **Challenges**
  - A sequence of events
  - Asynchronous and sparse



(a) Conventional camera (b) DVS

Fig.3 Event camera VS conventional camera.

- **Contribution**
  - BOE—feature extraction method based on probability theory
  - Online learning algorithm
  - Simple and competitive performance

2 Method

☐ Framework

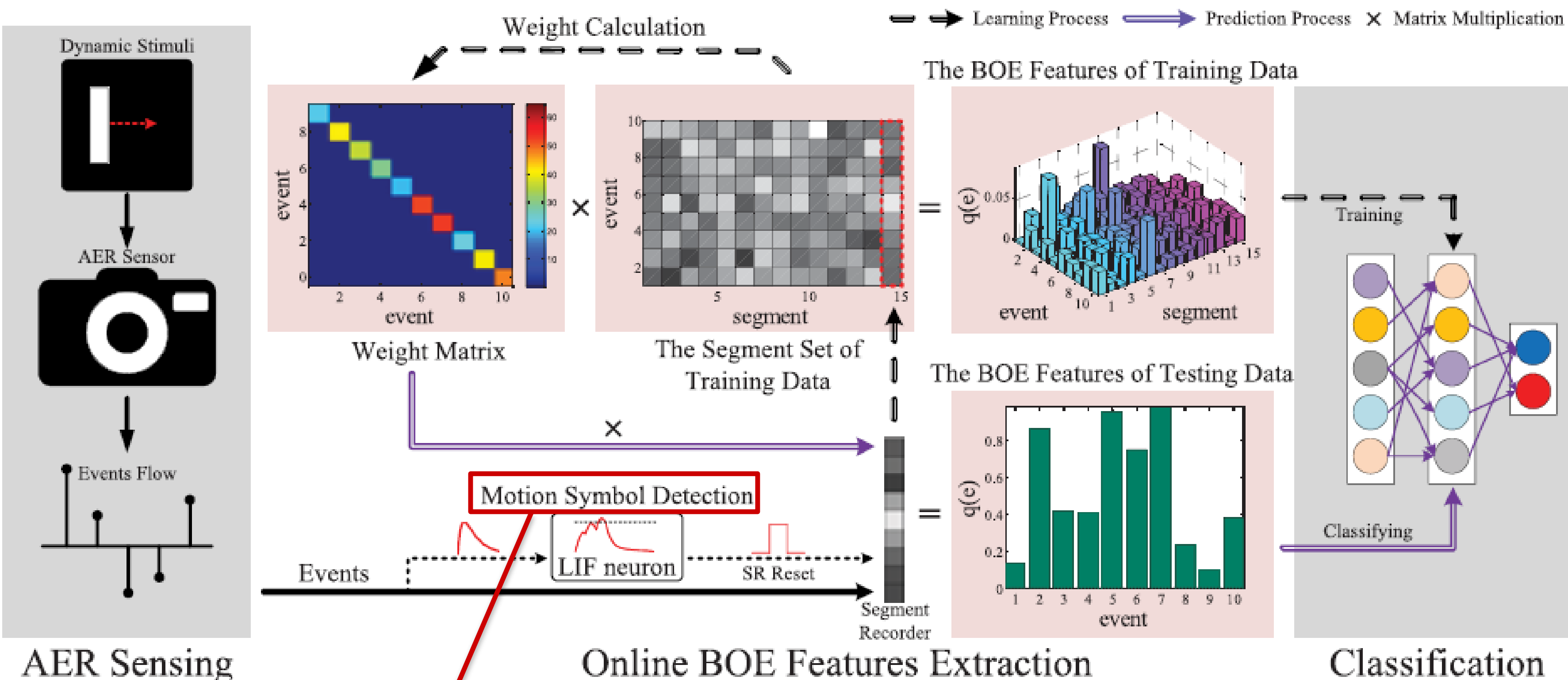


Fig.2 Architecture of the proposed system

Generating bags

2 Feature extracting

- **Bag of events**
  - LIF neural model

$$\mathcal{K}(t_i) = \exp\left(-\frac{t - t_i}{\tau}\right)$$

$$\mathcal{K}(t) = \sum_{t_i \in [t-1, t]} \mathcal{K}(t_i)$$

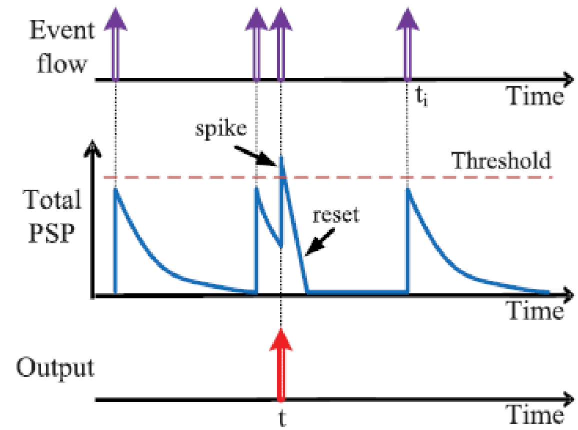


Fig.3 Dynamics of an LIF neuron

- **Event-based feature extracting**
  - Segments

$$\mathcal{S} = \{s_1, s_2, \ldots, s_n\}$$

  - Bag of events

$$\mathcal{E} = \{e_1, e_2, \ldots, e_m\}$$

  - Joint probability distribution

$$s_j = P(e_1, e_2, \ldots, e_m)$$

$$\boxed{[f_{1j}, f_{2j}, \ldots, f_{mj}]}$$

  - Feature representations

$$q_{ij} = w_i f_{ij}$$

$$\boxed{w_i = -\log \frac{n}{n_i}}$$

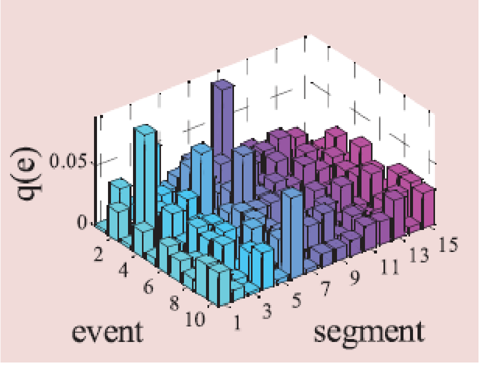


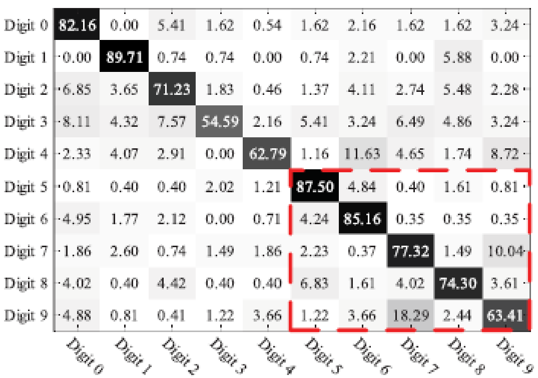
Fig.4 The BOE features

3 Experiments

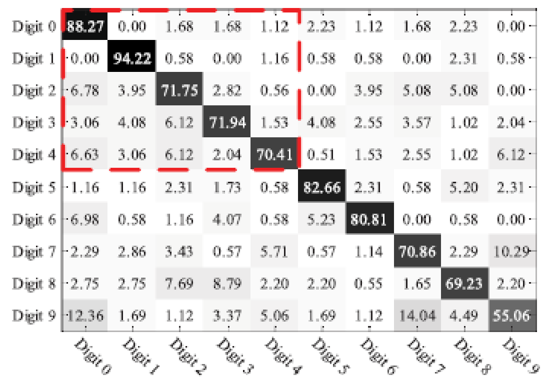
Classification accuracies

- MNIST-DVS

Tab. 1 Compared methods for MNIST-DVS database



BOE: 75.09%



Zhao et.al[1]: 73.35%

Chen et.al[2]: 61.23%

Complexity analysis

- Feature extraction and classification

Tab. 2 Compared methods for complexity analysis

Algorithms	Feature Extraction					Classification				
	training(s)	testing(s)	total(s)	fps	tpe(s)	training(s)	testing(s)	total(s)	fps	tpe(s)
BOE	**27.89**	**27.28**	**55.17**	**402.65**	**8.28E-06**	**3.63**	**0.12**	**3.75**	**5926.63**	**5.62E-07**
Zhao's [18]	8601.10	955.68	9556.78	1.87	1.17E-03	204.11	26.93	231.05	77.23	2.82E-05
Chen's [15]	1208.38	134.26	1342.64	16.69	2.00E-04	-	7691.26	7691.26	2.91	1.14E-03

[1] Feed-forward categorization on AER motion events using cortex-like features in a spiking neural network, Bo Zhao et.al, ***TNNLS*** 2015.
[2] Efficient feedforward categorization of objects and human postures with address-event image sensors, Shoushun Chen et.al, ***PAMI***, 2012.

4 Outlook

- 1 **Temporal information** can be feature representations?
- 2 **Local feature** representations?
- 3 **End-to-end SNN** used in spatial-temporal spike stream?

Overview

- Introduction
  - Event-based sensors
  - Related works
- Image representations
  - Steering prediction, CVPR 2018
- Time surface representations
  - HOTS, PAMI 2017
  - HATS, CVPR 2018
- Feature representations
  - Bag of Events, TNNLS 2017
- **End-to-end SNN**
  - STDP, TNNLS 2014
- Discussion
  - Better input representations for CNN
  - Event-based sensors future

Unsupervised learning of digit recognition using spike-timing-dependent plasticity

Peter U. Diehl *, and Matthew Cook

TNNLS, 2014

1 Introduction

Leaky-integrate-and-fire, LIF

- Firing model

$$\tau_m \frac{du}{dt} = -u(t) + RI(t)$$

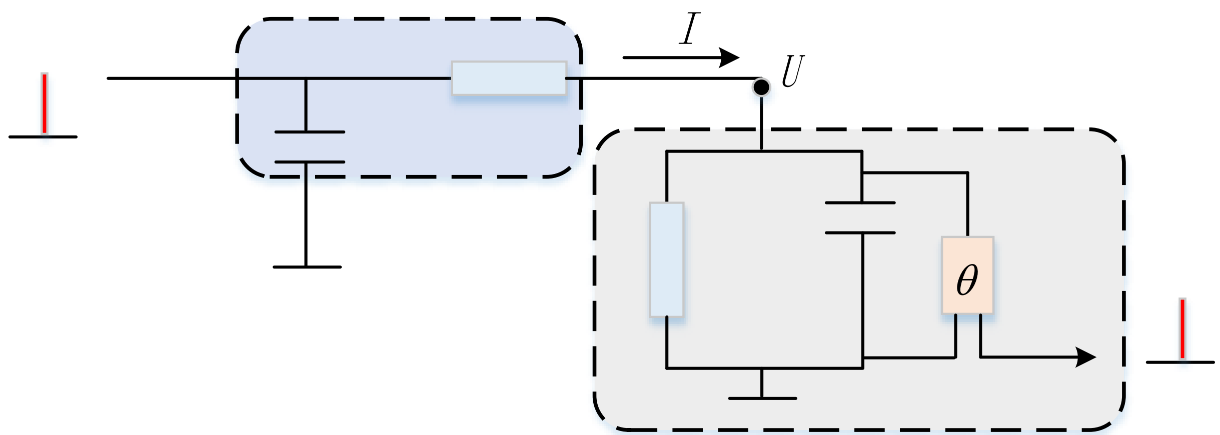


Fig.1 Leaky-integrate-and-fire model

1 Introduction

Spike-timing dependent plasticity, STDP

- Synapse plasticity

$$\left.\begin{aligned} \frac{dx_{pre}}{dt} &= -\frac{x_{pre}}{\tau_{pre}} \\ \frac{dx_{post}}{dt} &= -\frac{x_{post}}{\tau_{post}} \end{aligned}\right\} \quad \Delta w = \eta O(x_{pre}, x_{post})$$

- Synapse weight

$$\Delta w = \sum_{t_{pre}} \sum_{t_{post}} f(t_{post} - t_{pre})$$

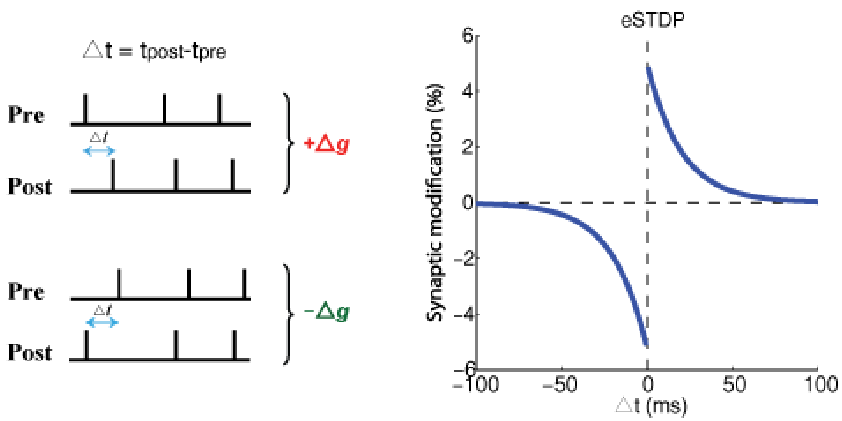


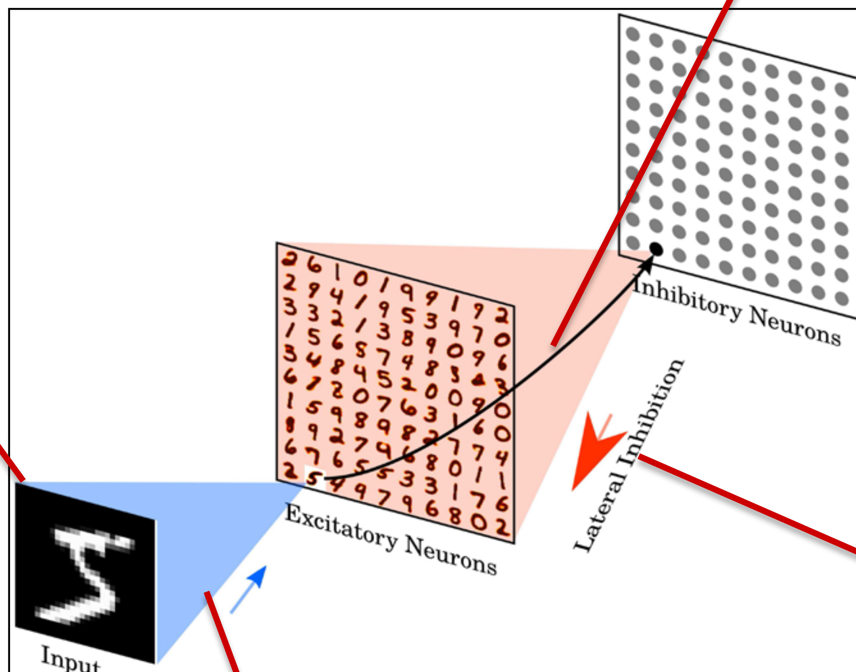
Fig.2 e-STDP learning function

2 Method

- **Network architecture**
  - **STDP called unsupervised learning**
  - How to use labels

One to one connections

Possion-spike with firing rates



Connected all except one

Fig.3 Two layers network

STDP learning rule

2 Method

Neuron and synapse model

- **LIF model**, the membrane voltage V [1]

$$\tau \frac{dV}{dt} = (E_{rest} - V) + g_e(E_{ext} - V) + g_i(E_{inh} - V)$$

Learning rule

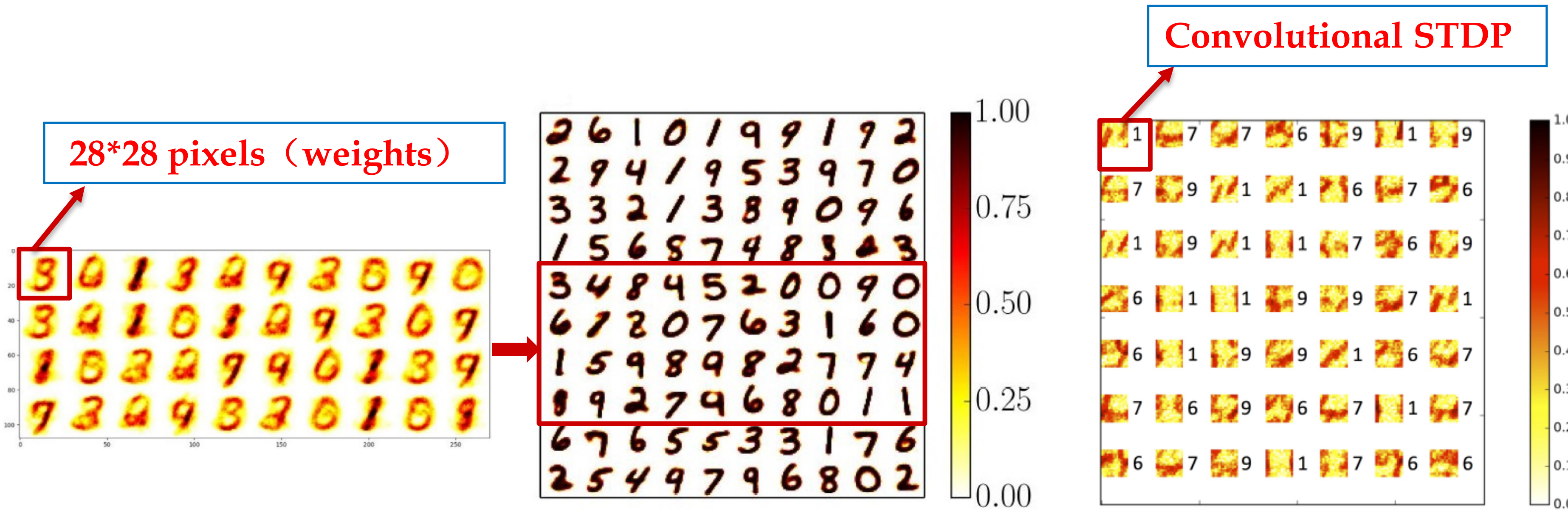
- Weight change

$$\Delta w = \eta\left(x_{pre} - x_{tar}\right)(w_{max} - w)^{\mu}$$

[1] Brian2 link: http://brian2.readthedocs.io/en/stable/index.html

2 Method

- **Train**
  - **Assigned excitatory neurons**



(a) 4*10 excitatory neurons (b) 10*10 excitatory neurons(400) (c) 7*7 excitatory neurons [2]

Fig.4 2D receptive fields

[2] Deep spiking convolutional neural network trained with unsupervised spike timing dependent plasticity. Chankyu Lee., TCDS, 2018.

3 Experiments

Results

Event-based data?

Architecture	Preprocessing	Training-type	(Un-)supervised	Learning-rule	Performance
Dendritic neurons (Hussain et al., 2014)	Thresholding	Rate-based	Supervised	Morphology learning	90.3%
Spiking RBM (Merolla et al., 2011)	None	Rate-based	Supervised	Contrastive divergence, linear classifier	89.0%
Spiking RBM (O'Connor et al., 2013)	Enhanced training set to 120,000 examples	Rate-based	Supervised	Contrastive divergence	94.1%
Spiking convolutional neural network (Diehl et al., 2015)	None	Rate-based	Supervised	Backpropagation	99.1%
Spiking RBM (Neftci et al., 2013)	Thresholding	Rate-based	Supervised	Contrastive divergence	92.6%
Spiking RBM (Neftci et al., 2013)	Thresholding	Spike-based	Supervised	Contrastive divergence	91.9%
Spiking convolutional neural network (Zhao et al., 2014)	Scaling, orientation detection, thresholding	Spike-based	Supervised	Tempotron rule	91.3%
Two layer network (Brader et al., 2007)	Edge-detection	Spike-based	Supervised	STDP with calcium variable	96.5%
Multi-layer hierarchical network (Beyeler et al., 2013)	Orientation-detection	Spike-based	Supervised	STDP with calcium variable	91.6%
Two layer network (Querlioz et al., 2013)	None	Spike-based	Unsupervised	Rectangular STDP	93.5%
Two layer network (this paper)	None	Spike-based	Unsupervised	Exponential STDP	95.0%

Tab.1 Classification accuracy of SNN on MNIST

4 Extended works

Experiments

- DVS-MNIST dataset

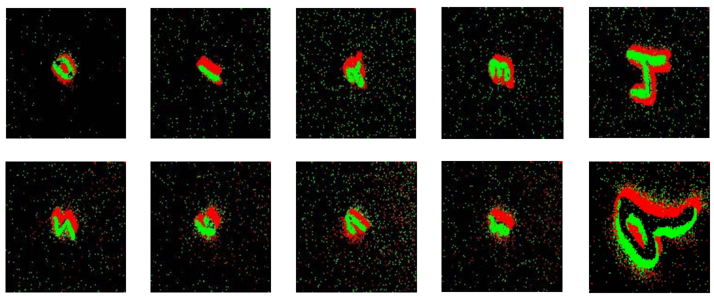


Fig.5 N-MNIST dataset

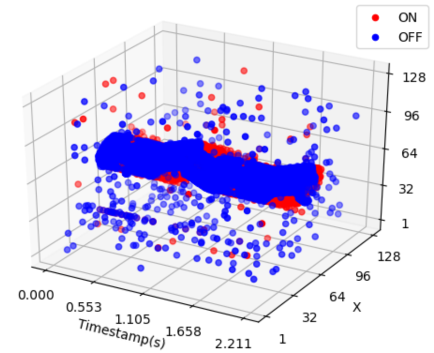


Fig.6 event streams

- Results comparison

Rate-based coding

Tab.2 Event-based classification on N-MNIST dataset

Methods	Author	Now work
STDP [NNLS, 2015][3]	-	0.913
HATS [CVPR, 2018][4]	**0.984**	<u>0.972</u>

[3] Unsupervised learning of digit recognition using spike-timing-dependent plasticity, Peter U. Diehl et. al, *TNNLS* 2014.
[4] HATS: Histograms of averaged time surfaces for robust event-based object classification, Amos Sironi, et. al, *CVPR* 2018.

5 Outlook

- 1 **No Brian2 , No Nest Simulation platform**, but in deep Architecture, such as Pytorch [5]?

- **2 End-to-end SNN** can be applied in complex event-based vision tasks?

- **3** Sparse lattice networks [6] used in spatial-temporal spike stream?

[5] Direct training for spiking neural networks: faster, larger, better, Yujie Wu et. al, ***arXiv*** 2018.
[6] Hnnge Su et.al . SPLATNet: Sparse Lattice Netorks for Point Cloud Processing. Hang su et.al, ***CVPR*** 2018.

6 Summary

Representations	Disadvantages	Advantages
Image	**Lack of temporal information**	**Deep learning**
Time surface	**Complexity & Local feature**	**Temporal information**
Feature	**Multi-steps**	**Complex vision tasks**
End-to-end SNNs	**Neural model + Framework**	**Temporal information**
End-to-end CNNs	**Lack of datasets** ***Waiting …***	**Complex vision tasks**

Tab.3 Representations for event-based camera data

Overview

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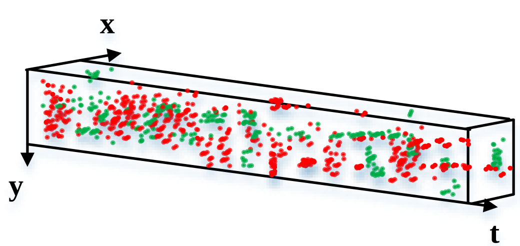
  - HATS, CVPR 2018
- Feature representations
  - Bag of Events, TNNLS 2017
- End-to-end SNN
  - STDP, TNNLS 2014
- **Discussion**
  - Better input representations for CNN
  - Event-based sensors future

Discussion

- **Better input representations for CNN**
  - Point process, such as **PointNet** [1]
  - **Lack of training dataset**

- **The future of event-based cameras**
  - Sparse and asynchronous events
  - Point process



[1] PointNet++: Deep hierarchical feature learning on point sets in a metric space. Charles R. Qi., NIPS, 2017.

Q&A?

Thanks !