Deep Spiking Neural Network for Visual Pattern Recognition

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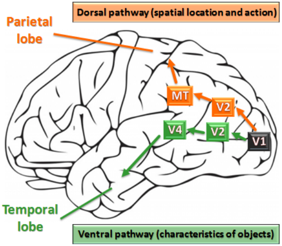
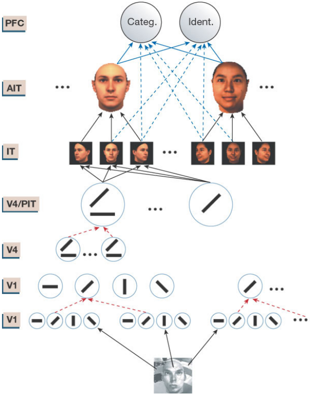
Outline

1. Introduction
2. Main Works
3. Future Works

Visual Pathway

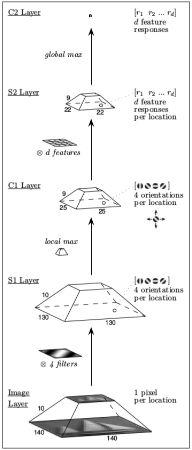
- Ventral stream





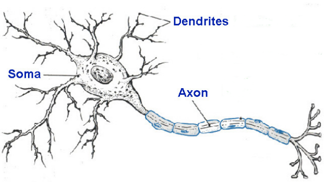
Deep Learning

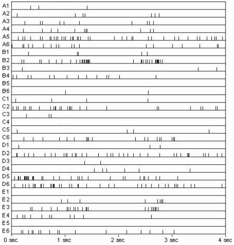
- Convolutional neural network (HMAX model)



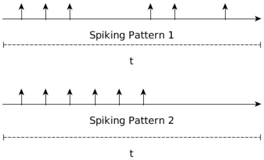
Spiking Neural Network

- Spiking neurons



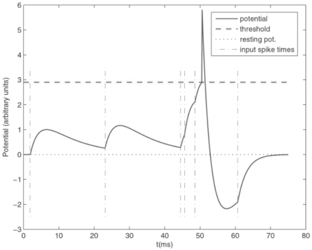


- ANN vs SNN



Neuron Model

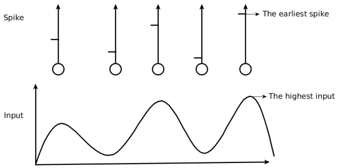
- Leaky integrate-and-fire (LIF) model



- Define neuron behaviors
- Coincidence detector

Spiking Coding Scheme

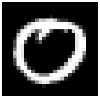
- Spiking rate vs spiking timing sequence
- Rank order coding (ROC)

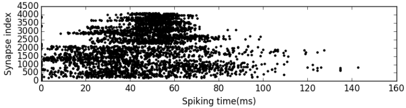


- Neuron is only allowed to fire at most once
- First spike wave is enough for further processing

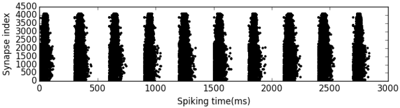
Spiking Coding Scheme

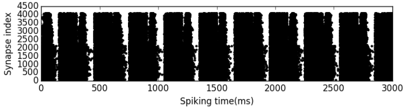
- One input image and its spiking pattern





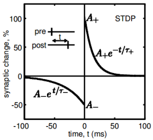
- Spiking pattern sequence

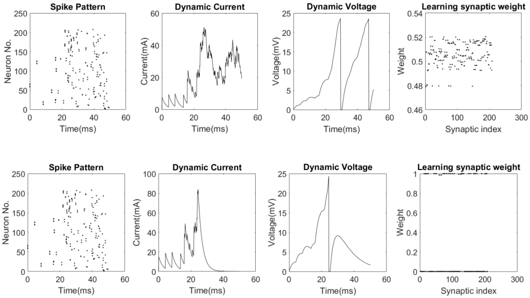




Learning Method

- Spike-timing dependent plasticity (STDP)



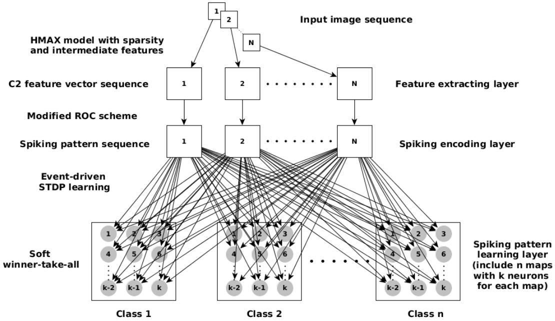


Event-driven Continuous STDP Learning (ECS)

- **State-of-the-art Methods**
- **Spiking rate-based models**
- Vanishing/exploding gradient problem
- Over-fitting, not robust
- Incorporate global error information
- Require long processing time
- Not biologically plausible
- **Spiking timing-based models**
- Require supervisory signal, no strong experimental confirmation
- STDP is used as a local feature extractor
- Not biologically plausible

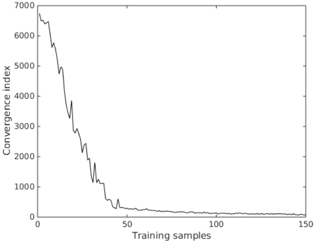
Event-driven Continuous STDP Learning (ECS)

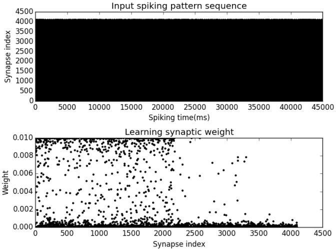
- ECS architecture



Event-driven Continuous STDP Learning (ECS)

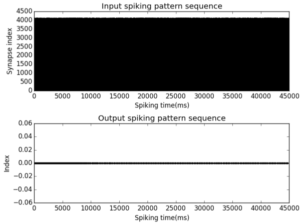
- Convergence analysis

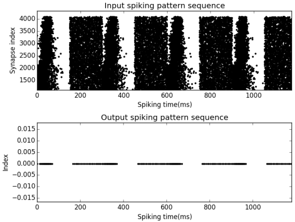


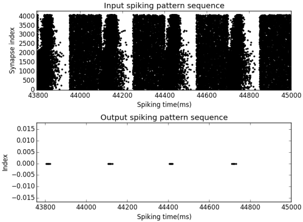


Event-driven Continuous STDP Learning (ECS)

- Robustness analysis







Event-driven Continuous STDP Learning (ECS)

- Experimental results

TABLE IV: Classification accuracy performance using different methods on MNIST database.

Spiking Coding-type	Architecture	Preprocessing	(Un-)supervised	Learning Rule	Performance: Simple random sampling [a]	Performance: Exhaustive [b]
Time-based	Spiking convolutional neural network	Modified HMAX	Supervised	**ECS(this paper)**	**89%**	**93.0%**
	Two layer network[10]	Simplified HMAX	Supervised	Tempotron rule	79.0%	N/A
	Two layer network[11]	Simplified HMAX	Supervised	Tempotron rule	N/A	91.3%
Rate-based	Dendritic neurons[4]	Thresholding	Supervised	Morphology learning	N/A	90.3% [d]
	Spiking RBM[5]	None	Supervised	Contrastive divergence, linear classifier	N/A	89.0%
	Spiking RBM[6]	Enhanced training set to 120,000 examples	Supervised	Contrastive divergence	N/A	89.0%
	Spiking convolutional neural network[7]	None	Supervised	Backpropagation	N/A	99.1%
	Spiking RBM[8]	Thresholding	Supervised	Contrastive divergence	N/A	92.6% [c]
	Spiking RBM[8]	Thresholding	Supervised	Contrastive divergence	N/A	91.9% [c]
	Two layer network[9]	Edge-detection	Supervised	STDP with calcium variable	N/A	96.5% [e]
	Multi-layer hierarchical neural network[1]	Orientation-detection	Supervised	STDP with calcium variable	N/A	91.6%
	Two layer network[2]	None	Unsupervised	Rectangular STDP	N/A	93.5%
	Two layer network[3]	None	Unsupervised	Exponential STDP	N/A	95.0%

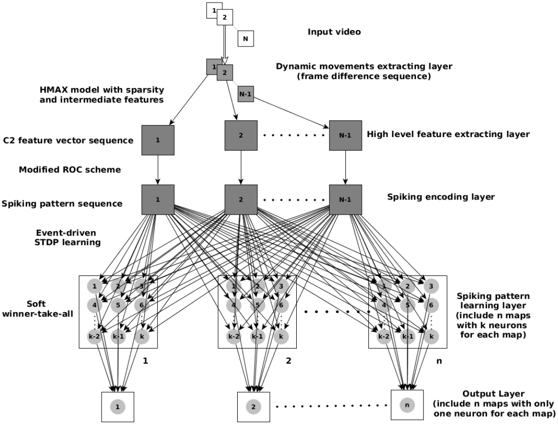
[a] Simple random sampling performance has been generated by averaging 10 random tests using 50 random training samples per class and 100 random testing samples, which is suitable for real-time learning since the whole database is impossible to obtain in most real scenarios.
[b] Exhaustive performance shows the ideal experimental results by using whole 60000 training samples and 10000 testing samples within MNIST database.
[c] The authors only use 1000 testing samples to obtain the performance
[d] The authors only use 5000 testing samples to obtain the performance
[e] The authors use 10000 randomly chosen samples from MNIST database instead of the dedicated testing database

Video-based Disguise Face Recognition (VDFR)

- **State-of-the-art VFR Methods**
- Set-based methods
- Sequence-based methods
- **Research Problems**
- It is often hard to obtain the ideal face frames
- Rely on the features which will be difficult to capture when there are invisible areas
- Does not incorporate disguise variations in current databases

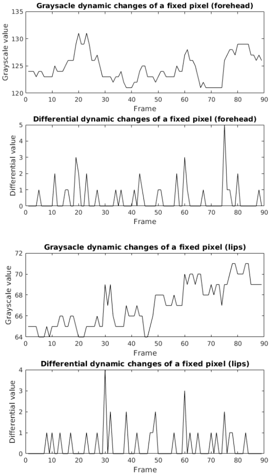
Video-based Disguise Face Recognition (VDFR)

- VDFR architecture



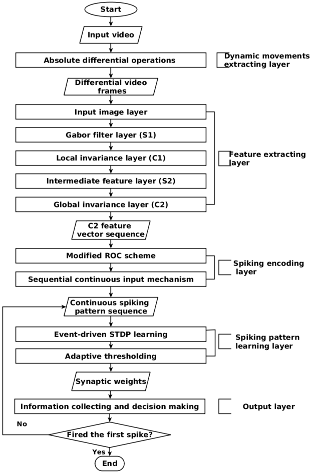
Video-based Disguise Face Recognition (VDFR)

- dynamic facial movements



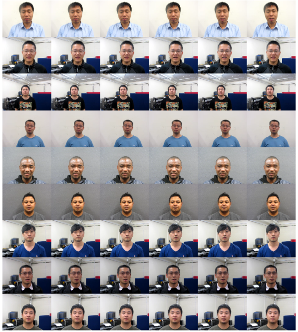
Video-based Disguise Face Recognition (VDFR)

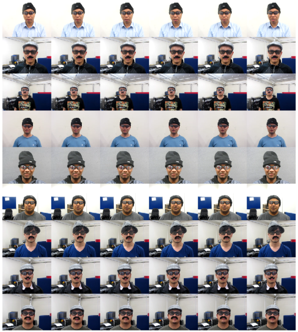
- Flowchart



Video-based Disguise Face Recognition (VDFR)

- MakeFace database





Video-based Disguise Face Recognition (VDFR)

- Experimental results

TABLE III: Correct classification performance using different number of training and testing video clips (%).

Number of training video clips	Number of testing video clips	Performance
1	4	92.5
2	3	100
3	2	100

TABLE IV: Classification performances of two different methods on testing video clips with disguise (%).

Method	Correct rate	Wrong rate	Unknown rate
CNN [29]	93.1 ± 1.35	6.9 ± 1.35	0
Proposed VDFR method	95.2 ± 2.65	4.8 ± 2.65	0

• Note: The classification rate has been computed by averaging 10 random tests. Furthermore, we have conducted a Wilcoxon signed-rank test on the correct classification performances by using the above two methods and computed the significance level $p-value$ (0.03429). Such significance level ($p-value < 0.05$) indicates that the two correct classification performances are statistically different.

TABLE V: Classification performances of two different methods on testing mixed video clips (%).

Method	Correct rate	Wrong rate	Unknown rate
CNN [29]	96.7 ± 0	3.3 ± 0	0
Proposed VDFR method	100 ± 0	0 ± 0	0

• Note: The classification rate has been computed by averaging 10 random tests.

TABLE VI: Classification performances of two different methods on testing unknown video clips (%).

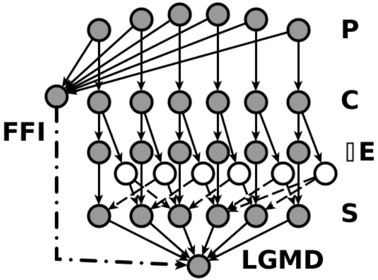
Method	Correct rate	Wrong rate	Unknown rate
CNN [29]	0	0	100 ± 0
Proposed VDFR method	0	0	100 ± 0

• Note: The classification rate has been computed by averaging 10 random tests.

A Spiking LGMD Model for Collision Detection

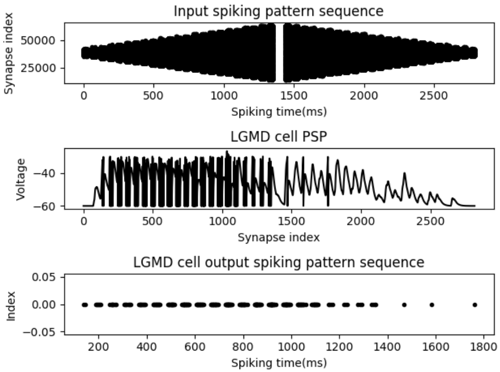
- **Research Problems of Current Models**
  - Only incorporate spiking concept in final decision making step
  - Do not incorporate spiking neural network during detection
  - Do not generate the collision selection observed in LGMD cell
- **Proposed model**
  - Add a spiking encoding layer behind the P layer
  - Incorporate a Poisson point process to generate spike trains
  - Spikes are the only accepted information medium
  - Use an exponential level conductance-based LIF model within S layer

A Spiking LGMD Model for Collision Detection

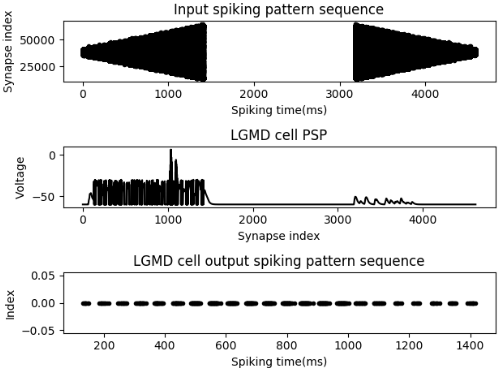


- Differentiate the post-synaptic membrane potentials generated when approaching and receding the object
- Generate a similar collision selection as the real LGMD cell
- Compare with current models, it is biologically plausible

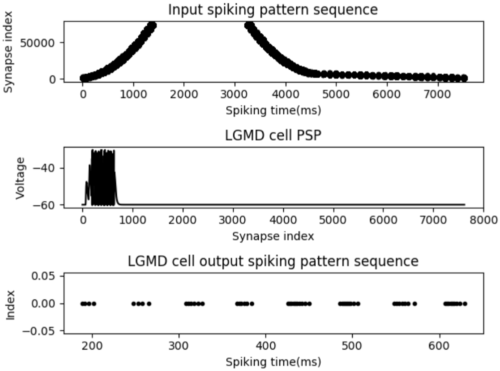
A Spiking LGMD Model for Collision Detection



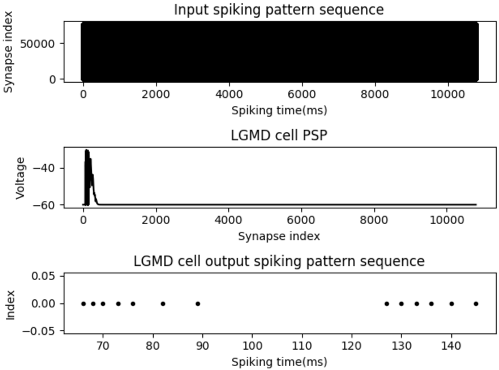
A Spiking LGMD Model for Collision Detection



A Spiking LGMD Model for Collision Detection



A Spiking LGMD Model for Collision Detection



Future Works

- Finish the spiking LGMD model for collision detection
- Investigate the proposed VDFR method against a complex moving background
- Propose an alternative competitive learning method to replace the current STDP learning rule

Thank you!