Biologically Plausible Training on Rate-based Spiking Autoencoders

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***Abstract*—How the brain works still remains a mystery and attracts researchers from various areas attempting to understand it. Nowadays, the exciting reports of the beating-human visual recognition and decision making have brought deep learning into the spotlight. It provides a clue which may unveil the mechanism of neural processing in the brain. Therefore, it becomes a hot topic to train and operate deep learning on spiking neural networks(SNN) underline the more biologically realistic way. This paper proposed a supervised learning rule to train the Autoencoders of spiking neurons using Spike-Timing-Dependent Plasticity (STDP). A network of two-layer Autoencoders was trained on the MNIST database with Integrate-and-Fire (IF) neurons. This results demonstrate the equivalent recognition capability comparing to the non-spiking implementations and validate the training ability of the learning rule of the biologically plausible spiking neurons.**

I. Introduction

Deep Neural Networks (DNNs) are the most promising research field in computer vision, even exceeding human-level performance on image classification tasks [1]. To investigate whether brains might work similarly on vision tasks, these powerful DNN models have been converted to spiking neural networks (SNNs). In addition, the spiking DNN offers the prospect of neuromorphic systems that combine remarkable performance with energy-efficient training and operation.

Theoretical studies have shown that biologically-plausible learning, e.g. Spike-Timing-Dependent Plasticity (STDP), could approximate a stochastic version of powerful machine learning algorithms [2], [3], [3], [4]. such as Expectation Maximization [2], Contrastive Divergence [3], Markov Chain Monte Carlo [5] and Gradient Descent [4]. Stochasticity, in contrast with the continuously differentiable functions used by ANNs, is intrinsic to the event-based spiking process, making network training difficult.

state-of-the-art of learning on SNN[6], [3], [7]

what's unique for the proposed method.

II. Background Knowledge

A. Autoencoders

B. IF Neuron

C. STDP Learning

III. Methods

A. Training Spiking Autoencoders

B. Convergence Evaluation

IV. Results

A. Classify MNIST Digits

B. Performance Evaluation

C. Trained weights

V. Conclusion

The conclusion goes here.

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