Improving STDP-based Visual Feature Learning with Whitening

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Abstract—In recent years, spiking neural networks (SNNs) emerge as an alternative to deep neural networks (DNNs). SNNs present a higher computational efficiency – using low-power neuromorphic hardware – and require less labeled data for training – using local and unsupervised learning rules such as spike timing- dependent plasticity (STDP). SNN have proven their effectiveness in image classification on simple datasets such as MNIST. However, to process natural images, a pre-processing step is required. Difference-of-Gaussians (DoG) filtering is typically used together with on-center / off-center coding, but it results in a loss of information that is detrimental to the classification performance. In this paper, we propose to use whitening as a pre-processing step before learning features with STDP. Experiments on CIFAR-10 show that whitening allows STDP to learn visual features that are closer to the ones learned with standard neural networks, with a significantly increased classification performance as compared to DoG filtering. We also propose an approximation of whitening as convolution kernels that is computationally cheaper to learn and more suited to be implemented on neuromorphic hardware. Experiments on CIFAR-10 show that it performs similarly to regular whitening. Cross-dataset experiments on CIFAR-10 and STL-10 also show that it is fairly stable across datasets, making it possible to learn a single whitening transformation to process different datasets.

Index Terms—Convolutional neural networks, Pattern recognition, Unsupervised learning

I. INTRODUCTION

In recent years, deep neural networks (DNNs) have become a de facto standard in machine learning, thanks to their ability to learn complex representations from large amounts of data. They have demonstrated their superiority over other models in a large number of tasks, including image and video classification, speech recognition, and natural language understanding. However, they suffer from two major drawbacks that hamper their adoption at a large scale. First, training a DNN is computationally expensive, due to its large number of parameters and the large amounts of data required to effectively estimate these parameters. As a consequence, DNNs training is usually performed on GPU or TPU that consume large quantities of energy. Moreover, DNNs mostly rely on supervised learning, which requires these large amounts of data (e.g., millions of samples in the case of image classification [14]) to be annotated manually beforehand, making them difficult to apply to new tasks, unless one is willing to spend large amounts of time and money on the labeling process. Spiking neural networks (SNNs) offer an alternative to DNNs; they can be implemented efficiently through low-power neuromorphic hardware [17], which would solve one issue of DNNs. The problem of data labeling can also be avoided – to some extent – through the use of unsupervised learning rules. Spike-timing-dependent plasticity (STDP) is one of those rules, that can enable effective unsupervised learning in SNNs [16] and is compatible with low-energy neuromorphic hardware [20].

In this paper, we are interested in the problem of visual feature learning through SNNs equipped with an STDP learning rule, with the long-term goal of producing end-to-end spiking architectures compatible with low-power, neuromorphic, hardware. Such a system includes the following steps: image pre-processing, neural coding of the pre-processed images into spikes, neuron and synapse models, learning rules, and finally the feature classifier; all these elements should ideally be implementable through neuromorphic hardware components. In [9], an in-depth study of STDP-based feature learning for image recognition was performed; it concluded that STDP-based SNNs cannot currently compete with more traditional neural networks models of visual feature learning (namely, auto-encoders), and pointed out some reasons for the ineffectiveness of SNNs, especially the pre-processing of images and the inhibition mechanisms.

In this paper, we specifically address the issue of image pre-processing for visual feature learning and natural image classification with STDP-based SNNs. STDP learns patterns of correlated spike timestamps from the input spike trains [16]. To be processed by STDP networks, natural images must first be pre-processed so that the spikes trains representing them can encode relevant visual information. Indeed, directly encoding pixel values as spikes, through either temporal or frequency coding, would lead to learning mostly patterns consisting of uniform regions of light colors; this has been empirically confirmed in [9] in the case of temporal coding. The most common way to circumvent this issue is to convert images to grayscale and to apply on-center / off-center coding [5], [12] (or some equivalent edge-extraction method such as Gabor filters [11]). This coding is inspired
by biological vision, and is also related to the SIFT keypoint detector widely used in computer vision [15]. It extracts edges from the images by applying a difference of Gaussians (DoG) filter (see Figure 1(b)). As a result, the spike trains now encode edge information, which is richer than raw pixel information. However, this prevents the STDP networks from learning also visual patterns based on colors, as standard deep neural networks do [4], [14]. Applying on-center / off-center coding to the R, G, and B color channels independently (see Figure 1) does not solve this issue, since it only allows to learn edge patterns specific to one of the three color channels rather than actual color patterns. It has been shown empirically in [9] that on-center / off-center coding, applied either to grayscale or color images, results in a loss of information that is detrimental to image classification.

In this work, we propose to use whitening as a single pre-processing step for processing natural images with STDP-based SNNs. Whitening is commonly used in computer vision as an image pre-processing method [4], [13], among other uses [10]. Generally speaking, whitening is a procedure used in statistics to standardize and de-correlate data; it projects the data into a new, orthonormal, space so that its components are centered, independent, and have unit variance. When applied to images, whitening discards first-order correlations, which correspond to the fact that pixels that are spatially close to each other tend to have similar values; visually, it highlights edges and high frequency features. It allows neural networks to learn non-trivial correlations between pixels [4].

The whitening transformation is typically computed from a dataset using principal component analysis (principal component analysis (PCA)) or zero component analysis (ZCA) [1], and applied to whole images. As we aim at training end-to-end STDP-based systems that can be implemented on energy-efficient hardware, whitening cannot be applied as is, for three reasons:

- learning a PCA or ZCA transformation on whole images is computationally expensive and involves operations on dense matrices that cannot be implemented simply through neuromorphic hardware;
- only applying a learned whitening transformation to whole images cannot be implemented efficiently through neuromorphic hardware either, because of the non-local nature of the transformation;
- the transformation is data-dependent, so a new transformation should be computed for every new dataset.

The use of whitening as a pre-processing step for SNN-based image analysis would only be valuable if these issues can be circumvented in some way.

Based on these observations, the contribution of this paper is three-fold.

1) We show that using whitening as a pre-processing step allows STDP to learn patterns that are similar to what standard deep neural networks can learn, and is superior to on-center / off-center coding when performing image classification based on features learned with STDP.

2) We propose an approximation of ZCA whitening based on convolution kernels, that can be pre-computed more efficiently and fits the constraints of neuromorphic hardware better. Experiments show that this approximation yields the same performances as standard ZCA whitening.

3) We show through cross-dataset experiments that it is possible to pre-compute a single whitening transformation on one dataset and apply it to other datasets with only little impact on the classification performance. The resulting transformation still outperforms significantly on-center / off-center coding.

II. RELATED WORK

a) SNN-based Visual Feature Learning: Image classification and visual feature learning with SNNs has received an increasing interest over the last years (see [21] for a recent survey on this topic). Most authors focus on simple datasets like MNIST, which offer limited challenges. Some models were evaluated on more complex datasets of natural images such as CIFAR-10, but they usually include training procedures that cannot be implemented on low-power neuromorphic hardware, the most common approach being to convert pre-trained DNN models to spiking models. Such models offer limited benefits over DNNs, since training the model is the most computationally expensive step. SNN models that can be trained on energy-efficient hardware are usually based on STDP learning rules. The performance of these models are still behind other models, especially DNNs; as a consequence, most work still focus on simple datasets, such as MNIST [9], [19], [22] and ETH-80 [11], [12]. This may be due to the difficulty of training multi-layer STDP networks: multi-layer models based on STDP [9], [12] have only been proposed very recently. Another reason is the difficulty to handle color natural images, due to the ineffectiveness of the on-center / off-center coding used to pre-process images [9]. As a result, complex datasets of natural images are seldom used to evaluate STDP-based SNNs; recent examples include the Caltech Faces/Motorbikes dataset [8], [12], and CIFAR-10, CIFAR-100 or STL-10 [9]. In this paper, we aim at improving the ability of STDP-based networks to learn from complex natural images and bringing their performance closer to their competitors.

b) Whitening for Feature Learning and Deep Learning: Whitening has been especially studied as a pre-processing step in unsupervised visual feature learning [4], [13]. The reported results were sometimes contradictory: Krizhevsky and Hinton [13] evaluated the role of whitening in image classification based either on raw pixels or on visual features learned with restricted Boltzmann machines (RBM), and concluded whitened images did not provide any improvement over using unwhitened images, whereas Coates et al. [4] reported significant and consistent improvements in classification performance when using whitened images to learn visual features with k-means, mixtures of Gaussians, auto-encoders, and RBM. Whatever the actual outcomes of whitening can be when using traditional algorithms, the debate is not relevant
with STDP-based SNNs, as learning from raw images is not an option in this case, as demonstrated in [2]. In addition to pre-processing input data, whitening can be used to normalize network activations between layers of a DNN [10], in a process similar to batch normalization. However, this is not related to our goal here, which is only to consider whitening as an alternative to on-center / off-center coding.

c) Whitening and SNNs: Whitening is seldom used as a pre-processing step to SNN. To our knowledge, only Burbank [2] used whitening as a pre-processing step before learning visual features from natural images with SNNs. No specific reason for the use of whitening was provided, other than re-using the data of Olshausen & Field [18]. The evaluation of the resulting features does not include recognition performance and the performance of whitening w.r.t. other pre-processing methods (e.g., on-center / off-center coding) was not assessed.

III. BACKGROUND

A. Unsupervised Feature Learning and Image Classification

The problem of image classification can be modeled as finding a function \( f: I \rightarrow \mathbb{C} \) which assigns to an image \( I \in \mathbb{I} \) the label \( c \in \mathbb{C} \) of the class it belongs to. A typical DNN-based approach would directly infer \( f \) from labeled training data. Other approaches model \( f \) as the composition of three individual functions: a feature extractor \( f_c \), a feature aggregator \( f_a \), and a supervised classifier \( f_r \). The feature extractor is a function \( f_c: I \rightarrow \mathbb{R}^{m \times d} \) that converts an image \( I \) into a set of \( m \) visual features representative of its visual content (shape, color...); each feature is modeled as a vector of dimension \( d \). The feature aggregator is a function \( f_a: \mathbb{R}^{m \times d} \rightarrow \mathbb{R}^{d'} \) that aggregates the \( m \) feature vectors into a single description vector of dimension \( d' \), typically through some pooling operation. Finally, the classifier \( f_r: \mathbb{R}^{d'} \rightarrow \mathbb{C} \) assigns a class \( c \in \mathbb{C} \) to an image \( I \in \mathbb{I} \) based on its aggregated feature vector \( f_a \circ f_c(I) \). In this work, the feature extractor \( f_c \) is a convolutional single-layer SNN that learns features from data using an unsupervised STDP learning rule. As we aim at evaluating only the ability of STDP to learn visual features, we rely on more classical tools for the feature aggregator \( f_a \) (max pooling) and the classifier \( f_r \). The details of our recognition system are provided in Section V-A.

B. SNN model

An STDP-based SNN typically includes the following components: a neural coding model, which converts input data into spikes, a spiking neuron model, an STDP learning rule, and homeostasis mechanisms that ensure that the activity of the network remains consistent. Since we are interested in learning visual features that will be used for classification, we also need a "neural decoding" model that converts output spikes back to numerical values that can be fed to the feature aggregator or the classifier. We use the same components as in of [8], which provide state-of-the-art performance for STDP-based visual feature learning.

a) Neural coding: We use latency coding [23], which is one variant of temporal coding, to convert input values \( x \) into spikes. Earlier spikes encode larger values. Spike timestamps are generated as follows:

\[
t = t_{\text{exposition}}(1 - x)
\]

with \( t \) the timestamp of the spike, \( x \) the converted input value, and \( t_{\text{exposition}} \) the duration of the exposition of an input sample to the network. As a consequence, there is at most one spike per input per sample.

b) Neuron model: The SNN uses integrate-and-fire (integrate-and-fire (IF)) neurons [3]. This model is defined as follows:

\[
e_m \frac{\partial v}{\partial t} = z(t), v \leftarrow v_{\text{rest}} \text{ when } v \geq v_{\text{th}}
\]

with \( v \) the membrane potential, \( v_{\text{rest}} \) the resting potential, \( e_m \) the membrane capacitance, \( v_{\text{th}} \) the threshold of the neuron, and \( z(t) \) the input current of the neuron \((z(t) = 1 \text{ if } v \leq v_{\text{th}} \text{ and } z(t) = 0 \text{ otherwise})\).

c) Synapse model: Every time a neuron fires a spike, the weights of its input connections are updated following a STDP rule, according to the activity of the corresponding presynaptic neurons. Multiplicative STDP [19] is used to train synaptic weights \( w \):

\[
\Delta_w = \begin{cases} 
\eta_w e^{-\beta \frac{w - w_{\text{min}}}{w_{\text{max}} - w_{\text{min}}}} & \text{if } t_{\text{pre}} \leq t_{\text{post}} \\
-\eta_w e^{-\beta \frac{w_{\text{max}} - w}{w_{\text{max}} - w_{\text{min}}}} & \text{otherwise}
\end{cases}
\]

with \( \eta_w \) the learning rate, \( w_{\text{min}} \) and \( w_{\text{max}} \) the minimum and maximum synaptic weights, and \( \beta \) the STDP time constant.
with \(w_{\text{min}}\) and \(w_{\text{max}}\) the bounds of the weight \(w\), \(\Delta_w\) the update applied the weight \((w_t = w_t + \Delta_w)\), \(\eta_w\) the learning rate, and \(t_{\text{pre}}\) and \(t_{\text{post}}\) the firing timestamps of the pre-synaptic and post-synaptic neurons, respectively. \(\beta\) is a parameter that controls the saturation effect of the learning rule (increasing \(\beta\) reduces the saturation of weights).

d) **Homeostasis:** Homeostasis in the network is maintained through the adaptation of neuron thresholds. Threshold values \(v_{\text{th}}\) are learned with the threshold adaptation proposed in [8] and a winner-takes-all (WTA) mechanism. Under this model, when a neuron wins the competition (i.e., it is the first one to fire a spike during the exposition of a sample), it applies the STDP rule to update its synaptic weights and it adapts its threshold \(v_{\text{th}}\) with the following update:

\[
\Delta_{\text{th}}^1 = \eta_{\text{th}},
\]

with \(\Delta_{\text{th}}^1\) the change applied to the neuron threshold \(v_{\text{th}}\) and \(\eta_{\text{th}}\) the learning rate of threshold adaptation. This rule ensures that a neuron will not always be the first to emit a spike.

The others neurons do not apply STDP and decrease their threshold as follows:

\[
\Delta_{\text{th}}^1 = -\frac{\eta_{\text{th}}}{|t_{\text{output}}|}
\]

with \(|t_{\text{output}}|\) the number of neurons in competition. This second update promotes diversity in neurons by lowering the threshold of neurons that emit few or no spikes.

Moreover, each time a winning neuron fires a spike, all the neurons in competition apply the following update to their threshold:

\[
\Delta_{\text{th}}^2 = -\eta_{\text{th}}(t - t_{\text{exp}})
\]

with \(\eta_{\text{th}}\) the threshold learning rate and \(t\) the timestamp at which the neuron fired the spike. \(T_{\text{exp}}\) is a manually-defined timestamp objective at which neurons should fire spikes. This parameter controls the number of input spikes to be integrated before an output spike is emitted, and, so, the nature of the filters to be learned [8], [9].

e) **Neural decoding:** Spikes generated at the output of the SNN can be converted back into values as follows:

\[
y = \min\left(1, \max\left(0, 1 - \frac{t - t_{\text{exp}}}{t_{\text{exposure}} - t_{\text{exp}}}\right)\right)
\]

C. **ZCA Whitening**

Whitening is a data-dependent transformation that decorrelates and standardizes the data. Several whitening transformations can exist for a given dataset, as whitened data remains whitened under rotations. Among these, zero-phase whitening (ZCA) [1] is the transformation that produces the whitened data that remains the closest to the original data. When applied to images, ZCA whitening produces images that are still recognizable by the human eye (as opposed to, for instance, PCA whitening).

Let \(X\) be a centered data matrix and \(\Sigma\) its covariance matrix. \(\Sigma\) can be decomposed so that:

\[
\Sigma = U \Lambda U^{-1}
\]

with \(U\) the matrix of eigenvectors of \(\Sigma\) and \(\Lambda\) the diagonal matrix of its eigenvalues \((\Lambda = \text{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n))\).

The ZCA transformation matrix \(W_{\text{whiten}}\) for data \(X\) is computed as follows:

\[
W_{\text{whiten}} = U \sqrt{(\Lambda + \epsilon)^{-1}} U^T
\]

with \(\epsilon\) the whitening coefficient, which adds numerical stability and acts as a low pass filter. As in PCA, it is possible to retain only the \(k\) largest eigenvalues and their corresponding eigenvectors, to eliminate the least significant components of the data, which may correspond to noise. In the remaining of the paper, we note \(\rho \in [0, 1]\) the ratio of the largest eigenvalues that are retained.

Finally, the ZCA whitened data \(X_{\text{whiten}}\) is computed from the ZCA transformation \(W_{\text{whiten}}\) as:

\[
X_{\text{whiten}} = W_{\text{whiten}} X
\]

IV. Contribution

A. **Encoding Whitened Data as Spikes**

The first part of our contribution is to enable the conversion of whitened data into spikes. The output of the whitening transformation contain both positive and negative values, which correspond to the positive or negative contribution of the data to the components of the transformation; larger values correspond to larger contributions, i.e. they are more significant. These values must be converted into spikes while respecting the principle of temporal coding: larger values must be converted into the earlier spikes. Similarly to on-center / off-center coding, we split the values into two channels, a positive one and a negative one. The conversion process follows these steps:

1) The data matrix \(X\) is whitened using the learned ZCA transformation.

2) The components of each sample in \(X_{\text{whiten}}\) are scaled in \([-1, 1]\) according to the minimum and maximum values of the sample.

3) Positive and negative values are split into two channels \(X_+\) and \(X_-\): \(X_+ = \max(0, X_{\text{whiten}})\), \(X_- = \max(0, -X_{\text{whiten}})\).

The values can finally be converted into spikes by using latency coding (Equation 1).

B. **Approximating whitening with convolution kernels**

Applying the whitening transformation to images is computationally expensive and is not easily implementable on neuromorphic architectures. In opposition, the DoG filter of on-center / off-center coding is a pre-processing, which is already well-used with SNNs, can be computed by simply convolving an image with an appropriate kernel. In this section, we show how to approximate whitening by convolution kernels, to benefit both from the ease of implementation of DoG filtering and from the performance of whitening. Our approach also reduces the cost of learning the whitening transformation matrix.
Fig. 2: Examples of whitening kernels approximating the ZCA transformation.

The general idea is to learn the whitening transform on small patches rather whole images, then to approximate the patch whitening transformation by the whitening transformation of a single pixel within the patches, which can be expressed as a convolution kernel. First, \( n_{\text{patches}} \) patches of size \( p_{\text{width}} \times p_{\text{height}} \) are extracted from the dataset (e.g. using dense or random sampling). A ZCA transformation matrix \( W_{\text{whiten}} \) of dimension \( [p_{\text{width}} \times p_{\text{height}} \times x_{\text{depth}}, p_{\text{width}} \times p_{\text{height}} \times x_{\text{depth}}] \) is computed from these patches. Finally, \( W_{\text{whiten}} \) is converted into \( x_{\text{depth}} \) kernels \( K_c \) of dimension \( [p_{\text{width}}, p_{\text{height}}] \). To do so, an impulse response matrix \( J \) is created for each \( x_{\text{depth}} \) channel with only its central value in channel \( c \) set to 1:

\[
J_c(i, j, k) = \begin{cases} 
1 & \text{if } k = c \text{ and } i = \frac{p_{\text{width}}}{2} \text{ and } j = \frac{p_{\text{height}}}{2} \\
0 & \text{otherwise} 
\end{cases}
\]

with \( i \in [0, p_{\text{width}}] \), \( j \in [0, p_{\text{height}}] \), and \( k \in [0, x_{\text{depth}}] \) the coordinates in matrix \( J \) and \( c \in [0, x_{\text{depth}}] \) the corresponding channel.

A whitening kernel can be computed for each channel \( c \) as:

\[
K_c = J_c W_{\text{whiten}}
\]

and an image can be whitened by convolving each of its channels with the corresponding whitening kernel. Each whitening kernel \( K_c \) corresponds to the whitening transformation of the central pixel of a channel of the patches. Examples of whitening kernels generated by this method and the resulting filtered images are shown in Figure 2.
Fig. 3: Recognition system used in our experiments.

![Recognition System Diagram]

Fig. 4: Classification performance on CIFAR-10 with standard whitening (a) vs whitening kernels (b).

![Classification Performance Graph]

**TABLE I: Default parameters used in the experiments.**

| Neural Coding               |   |
|-----------------------------|--|
| t<sub>exp</sub>             | 1 |
| Neuron                      |   |
| V<sub>th</sub>(0)           | G(10, 0.1) |
| V<sub>rest</sub>            | 0 |
| Threshold Adaptation        |   |
| t<sub>exp</sub>             | 0.97 |
| η<sub>th</sub>(0)           | 1 |
| Training                    |   |
| α                           | 0.95 |
| n<sub>epoch</sub>           | 100 |
| STDP                        |   |
| w<sub>min</sub>             | 0 |
| w<sub>max</sub>             | 1 |
| η<sub>w</sub>(0)            | 0.1 |
| V<sub>(0)</sub>             | ~ U(0, 1) |
| β                           | 1 |

Network architecture
- Filter size: 5 x 5
- Stride: 1
- Padding: 0

**B. Standard Whitening vs Whitening Kernels**

In this section, we compare the performance of standard whitening and the whitening kernels in terms of the classification performance of our system (see Figure 3). Experiments have been conducted by varying the major parameters: t<sub>exp</sub> and the number of filters used in the convolution layer.

Figure [4] shows that the behavior of both whitening processes is fairly similar. The reported performances of whitening kernels were obtained using 9 x 9 patches, e = 10<sup>-2</sup> and ρ = 1.0. The performances achieved for each t<sub>exp</sub> and for each number of filters considered are similar. This shows that the approximation of the whitening transformation by convolution kernels performs as well as the original whitening transform. For both methods, t<sub>exp</sub> seems to be optimal around 0.96.

An in-depth exploration of the parameters of whitening kernels (patch size, whitening coefficient e, and ratio of eigenvectors ρ) was conducted. Table [II] shows the results obtained with various kernel sizes, e, and numbers of learned filters (l<sub>output</sub>). Several observations can be drawn from these results. First, with 64 filters, the performances are overall lower than with 256. However, no strong improvement is observed when using 1024 learned filters. Second, for each configuration using a fixed number of filters, the performances are quite stable regardless of patch size. However, overall, slightly better average performances are obtained when the patch size increases (see 9 x 9 and 11 x 11 configurations). A value of 10<sup>-2</sup> for the whitening coefficient e seems more adequate when more filters are used.

Table [III] reports the performances with varying patch sizes, ρ, and numbers of learned filters. Among all configurations
TABLE III: Recognition rate (%) w.r.t. patch size and $\epsilon$ ($\rho = 1.0$).  

| $|l_{output}|$ | $|l_{patch}\text{, }\text{whitn.}$ | 10$^{-1}$ | 10$^{-2}$ | $\epsilon$ | 10$^{-3}$ | 10$^{-4}$ |
|------------|---------------------------------|--------|--------|-------|--------|--------|
| 64         |                                 |        |        |       |        |        |
| 5 x 5      | 51.36 ± 0.48 56.3 ± 0.09 53.49 ± 0.09 49.89 ± 0.77 |        |        |       |        |        |
| 7 x 7      | 53.04 ± 0.31 56.74 ± 0.21 54.93 ± 0.29 49.74 ± 0.88 |        |        |       |        |        |
| 9 x 9      | 53.07 ± 0.27 57.04 ± 0.10 60.13 ± 0.28 49.96 ± 1.12 |        |        |       |        |        |
| 11 x 11    | 53.65 ± 0.14 57.04 ± 0.05 55.2 ± 0.29 50.29 ± 0.44 |        |        |       |        |        |
| 256        |                                 |        |        |       |        |        |
| 5 x 5      | 59.32 ± 0.02 62.02 ± 0.16 58.62 ± 0.3 54.46 ± 0.27 |        |        |       |        |        |
| 7 x 7      | 60.05 ± 0.26 62.55 ± 0.19 58.76 ± 0.61 54.56 ± 0.27 |        |        |       |        |        |
| 9 x 9      | 59.81 ± 0.39 63.72 ± 0.39 59.12 ± 0.34 54.62 ± 0.18 |        |        |       |        |        |
| 11 x 11    | 60.13 ± 0.29 62.83 ± 0.63 58.99 ± 0.19 55.19 ± 0.56 |        |        |       |        |        |
| 1024       |                                 |        |        |       |        |        |
| 5 x 5      | 60.13 ± 0.37 62.91 ± 0.34 57.98 ± 0.2 53.94 ± 0.13 |        |        |       |        |        |
| 7 x 7      | 60.17 ± 0.24 63.63 ± 0.51 58.47 ± 0.67 54.29 ± 0.29 |        |        |       |        |        |
| 9 x 9      | 60.72 ± 0.37 63.78 ± 0.13 58.71 ± 0.45 53.54 ± 0.42 |        |        |       |        |        |
| 11 x 11    | 61.18 ± 0.07 62.91 ± 0.34 58.87 ± 0.55 53.87 ± 0.64 |        |        |       |        |        |

TABLE II: Recognition rate (%) w.r.t. patch size and $\epsilon$ ($\rho = 1.0$).  

| $|l_{output}|$ | $|l_{patch}\text{, }\text{whitn.}$ | 0.25 | 0.50 | 0.75 | 1.00 |
|------------|---------------------------------|------|------|------|------|
| 64         |                                 |      |      |      |      |
| 5 x 5      | 50.44 ± 0.28 55.99 ± 0.11 55.85 ± 0.17 56.17 ± 0.44 |      |      |      |      |
| 7 x 7      | 53.32 ± 0.45 56.83 ± 0.04 56.72 ± 0.17 56.60 ± 0.23 |      |      |      |      |
| 9 x 9      | 54.64 ± 0.06 56.88 ± 0.16 57.11 ± 0.19 56.86 ± 0.03 |      |      |      |      |
| 11 x 11    | 55.76 ± 0.07 57.28 ± 0.23 57.12 ± 0.28 57.33 ± 0.06 |      |      |      |      |
| 256        |                                 |      |      |      |      |
| 5 x 5      | 57.75 ± 0.03 61.60 ± 0.04 61.53 ± 0.20 61.95 ± 0.37 |      |      |      |      |
| 7 x 7      | 59.43 ± 0.45 62.19 ± 0.17 62.25 ± 0.14 62.41 ± 0.36 |      |      |      |      |
| 9 x 9      | 60.00 ± 0.07 62.37 ± 0.39 62.57 ± 0.10 62.41 ± 0.21 |      |      |      |      |
| 11 x 11    | 61.35 ± 0.29 62.56 ± 0.91 62.97 ± 0.28 62.70 ± 0.63 |      |      |      |      |
| 1024       |                                 |      |      |      |      |
| 5 x 5      | 57.9 ± 0.30 62.87 ± 0.32 62.80 ± 0.35 62.88 ± 0.45 |      |      |      |      |
| 7 x 7      | 59.24 ± 0.44 63.4 ± 0.19 63.49 ± 0.44 63.63 ± 0.28 |      |      |      |      |
| 9 x 9      | 59.11 ± 0.27 63.70 ± 0.09 63.39 ± 0.46 63.61 ± 0.38 |      |      |      |      |
| 11 x 11    | 60.71 ± 0.46 62.87 ± 0.32 63.72 ± 0.42 63.82 ± 0.45 |      |      |      |      |

TABLE III: Recognition rate (%) w.r.t. patch size and $\rho$ ($\epsilon = 10^{-2}$).  

These results show that the benefits brought by whitening kernels are stable and can generalize to a wide set of settings.

C. On-center / Off-center Filtering vs Whitening

Table [IV] compares the performances on CIFAR-10 of whitening to the baseline on-center / off-center coding, for $|l_{output}| = 64$ features and $|l_{output}| = 1024$ features. Whitening provides much better results than color on-center / off-center coding: +18% (+9 percentage points) with 64 filters and +11% (+6 pp.) with 1,024 filters. This may be due to its ability to retain color information and all spatial frequencies, whereas on-center / off-center coding only encodes edge information and a limited range of spatial frequencies.

| Method                     | 64 filters | 1,024 filters |
|---------------------------|------------|---------------|
| On-center / off-center (grayscale) | 45.37%     | 52.77%        |
| On-center / off-center (color)     | 48.27%     | 56.93%        |
| Standard whitening          | 57.66%     | 63.37%        |
| Whitening kernels           | 57.07%     | 63.64%        |

TABLE IV: Performance of whitening versus on-center / off-center coding on CIFAR-10.
TABLE V: Performances obtained in a cross-dataset configuration (first header row: dataset used for classification, second header row: dataset used to generate the whitening kernels. from CIFAR-10 and STL-10, respectively. Then, the CIFAR-10 dataset is pre-processed using whitening kernels learned on STL-10, and reversely. Each whitened dataset is then fed into our classification system and its accuracy is measured.

Table V shows the result obtained using different configurations. We used several numbers of filters. We fixed the following parameters: (a) \( \rho = 1 \); (b) \( \epsilon = 10^{-2} \), and (c) patch size \( = 9 \times 9 \). We report the results obtained either using whitening kernels computed on the same dataset or whitening kernels computed on the other dataset. Regardless of the underlying configuration, the difference of the recognition rates between whitening kernels trained on same dataset and trained on a different datasets is negligible. In almost all cases, the difference between the two configurations is close to zero or statistically not significant (smaller than the standard deviation). Thus, whitening kernels are dataset independent and can be computed once, an reused on multiple datasets.

VI. CONCLUSION

SNNs trained with STDP are good candidates to produce ultra-low power neural networks. However, their performances is currently far behind DNNs. Notably, STDP cannot learn effective features on real-word color images. On-center / off-center coding, used to pre-process images in this context, is partially responsible for it, as filters only a subrange of spatial frequencies from the original images. In this paper, we showed that pre-processing images with whitening allows to learn more effective features, closer to the ones learned with standard neural networks. Implementing whitening on neuromorphic hardware may not be trivial, so we also propose to approximate whitening with convolution kernels to facilitate its implementation. It yields almost the same performance as traditional whitening. Cross-dataset experiments show stable performance of the whitening kernels over datasets, making it possible to learn a single set of kernels to process different datasets, making it even more suitable in a low-power context.

REFERENCES

[1] Anthony J. Bell and Terrence J. Sejnowski. The independent components of natural scenes are edge filters. *Vision Research*, 37(23):3327 – 3338, 1997.

[2] Kendra S. Burbank. Mirrored stdp implements autoencoder learning in a network of spiking neurons. *PLoS computational biology*, 11(12):1–25, 2015.

[3] Anthony N Burkitt. A review of the integrate-and-fire neuron model: I. homogeneous synaptic input. *Biological Cybernetics*, 95(1):1–19, March 2006.

[4] Adam Coates, Andrew Ng, and Honglak Lee. An analysis of single-layer networks in unsupervised feature learning. In *International Conference on Artificial Intelligence and Statistics (AISTATS)*, volume 15, pages 215–223. PMLR, April 2011.

[5] Arnaud Delorme, Laurent Perrinet, and Simon J. Thorpe. Networks of integrate-and-fire neurons using rank order coding b: Spike timing dependent plasticity and emergence of orientation selectivity. *Neurocomputing*, 38:539–545, June 2001.

[6] Peter U Diehl and Matthew Cook. Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in Computational Neuroscience*, 9:1–9, August 2015.

[7] Pierre Fazel. *Improving Spiking Neural Networks Trained with Spike Timing Dependent Plasticity for Image Recognition*. PhD thesis, Université de Lille, October 2019.

[8] Pierre Fazel, Pierre Tirilly, Ioan Marius Bilasco, Philippe Devienne, and Pierre Boulet. Multi-layered spiking neural network with target times-tamp threshold adaptation and stdp. In *International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, July 2019.

[9] Pierre Fazel, Pierre Tirilly, Ioan Marius Bilasco, Philippe Devienne, and Pierre Boulet. Unsupervised visual feature learning with spike-timing-dependent plasticity: How far are we from traditional feature learning approaches? *Pattern Recognition*, 93:4184–2019.

[10] Lei Huang, Dawei Yang, Bo Lang, and Jia Deng. Decorrelated batch normalization. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Salt Lake City, UT, USA, June 2018.

[11] Saeed Reza Kheradpisheh, Mohammad Ganjtabesh, and Timothée Masquelier. Bio-inspired unsupervised learning of visual features leads to robust invariant object recognition. *Neurocomputing*, 205:382–392, September 2016.

[12] Saeed Reza Kheradpisheh, Mohammad Ganjtabesh, Simon J Thorpe, and Timothée Masquelier. STDP-based spiking deep convolutional neural networks for object recognition. *Neural Networks*, 99:56–67, March 2018.

[13] Alex Krizhevsky. Learning multiple layers of features from tiny images. Technical report, University of Toronto, April 2009.

[14] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. ImageNet classification with deep convolutional neural networks. In *Proceedings of the International Conference on Neural Information Processing Systems (NIPS)*, page 1097105, 2012.

[15] David G Lowe. Distinctive image features from scale-invariant keypoints. *International journal of computer vision*, 60(2):91–110, November 2004.

[16] Timothe Masquelier, Rudy Guyonneau, and Simon J. Thorpe. Spike timing dependent plasticity finds the start of repeating patterns in continuous spike trains. *PLoS One*, 3(1), January 2008.

[17] Paul A Merolla, John V Arthur, Rodrigo Alvarez-Icaza, Andrew S Cassidy, Jun Sawada, Filipp Akopyan, Bryan L Jackson, Nabil Imam, Chen Guo, Yutaka Nakamura, Bernard Brezzo, Ivan Vo, Steven K Esser, Rathinakumar Appuswamy, Brian Tabar, Arnon Amir, Myron D Flickner, William P Risk, Rajit Manohar, and Dharmendra S Modha. A million spiking-neuron integrated circuit with a scalable communication network and interface. *Science*, 345(6197):668–673, August 2014.

[18] Bruno Olshausen and David Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 381:607–9, 07 1996.

[19] Damien Quefioz, Olivier Bichler, and Christian Gamrat. Simulation of a memristor-based spiking neural network immune to device variations. *PLoS computational biology*, 11(12):1–25, 2015.

[20] Catherine D Schuman, Thomas E Potok, Robert M Patton, J Douglas Birdwell, Mark E Dean, Garrett S Rose, and James S Plank. A survey of neuromorphic computing and neural networks in hardware. *CoRR*, abs/1705.06963:1–88, May 2017.

[21] Amirhossein Tavanaei, Masoud Ghodrat, Saeed Reza Kheradpisheh, Timothée Masquelier, and Anthony Maida. Deep learning in spiking neural networks. *Neural Networks*, 111:47 – 63, 2019.

[22] Amirhossein Tavanaei and Anthony S Maida. Bio-inspired spiking convolutional neural network using layer-wise sparse coding and STDP learning. *CoRR*, abs/1611.03000, June 2017.

[23] Simon Thorpe, Arnaud Delorme, and Rufin Van Rullen. Spike-based strategies for rapid processing. *Neural Networks*, 14(6):715–725, July 2001.