

ClassONN: Classification with Oscillatory Neural Networks using the Kuramoto Model

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Abstract—Over the recent years, networks of coupled oscillators or oscillatory neural networks (ONNs) emerged as an alternative computing paradigm with information encoded in phase. Such networks are intrinsically attractive for associative memory applications such as pattern retrieval. Thus far, there are few works focusing on image classification using ONNs, as there is no straightforward way to do it. This paper investigates the performance of a neuromorphic phase-based classification model using a fully connected single layer ONNs. For benchmarking, we deploy the ONN on the full set of 28x28 binary MNIST handwritten digits and achieve around 70% accuracy on both training and test set. To the best of our knowledge, this is the first effort classifying such large images utilizing ONNs.

Index Terms—Image classification, oscillatory Hopfield neural networks, Kuramoto model

I. INTRODUCTION

Image classification is considered as one of the most classical edge artificial intelligence problems. Typically, one turns to convolutional neural networks (CNNs) to solve such tasks [1]. This paper investigates a new model for classification via coupled oscillators called oscillatory neural network (ONN).

This single layered network of fully connected oscillators is based on Hopfield neural networks [2, 3]. Despite particularly exceling at auto-associative memory tasks, further research needs to be done on these energy-based models regarding classification. Authors in [4, 5] were the first to investigate how to use HNNs and ONNs for classification.

Belyaev et al. [4] performed pattern classification with HNNs on binary pre-processed 14x14 MNIST digits achieving an accuracy of 61%. Similarly, Abernot et al. [5] used HNNs and ONNs to classify binary pre-processed 10x10 MNIST digits to reach precisions of 67% and 62.6%, respectively.

This paper expands on the two aforementioned papers by introducing ClassONN, a classification model with ONNs utilizing the Kuramoto neuron model to classify the full 28x28 MNIST binary data set. There are countless attempts at benchmarking on this dataset with CNNs or other various models [6, 7, 8], though to the best of our knowledge, this is the first attempt at classifying the whole MNIST dataset with ONNs.

II. BACKGROUND

A. Oscillatory neural networks

Oscillatory neural networks comprise fully coupled neurons in a single layer. Being based on the Ising model [9, 10], the aim lies in minimizing the following underlying Hamiltonian:

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$$H = - \sum_{(i,j)} J_{ij} \sigma_i \sigma_j - \mu \sum_i h_i \sigma_i \quad (1)$$

Given some couplings J_{ij} and a magnetic field \vec{h} , the aim is to find an arrangement of binary spins σ_i which minimizes H . This corresponds to finding the state the system naturally strives to evolve into. The evolution of oscillators can be expressed by neuron models, Kuramoto being one of them [11, 12].

B. Kuramoto model

The dynamics of a phase-locked loop neural networks in the phase model can be described by the following ODE [13]:

$$\dot{\theta}_i = \omega + V(\theta_i) \sum_{j=1}^n W_{ij} V(\theta_j - \frac{\pi}{2}) \quad (2)$$

The phases θ_i of oscillators are coupled through W with ω standing for the natural frequency of the system. Being derived based on the phase response curves (PRC) of the system, $V(\theta)$ is an odd 2π -periodic waveform function.

In the Kuramoto model, $V(\theta)$ is a sinusoidal function. By using phase deviations ϕ_i (derived with $\theta_i(t) = \omega t + \phi_i$) and introducing the subharmonic injection locking (SHIL) with K_S being its scaling factor, we rewrite Eq. 2 in the following way:

$$\dot{\phi}_i = \frac{1}{2} \sum_{j=1}^n W_{ij} \sin(\phi_j - \phi_i) - K_S \sin(2\phi_i) \quad (3)$$

III. IMAGE CLASSIFICATION WITH KURAMOTO

Generally, machines work with binary values $[+1, -1]$. Regarding oscillators, the phases $[0^\circ, 180^\circ]$ of the waves encode these binary values. Figure 1 illustrates the idea behind assigning binary values to oscillators based on their phases.

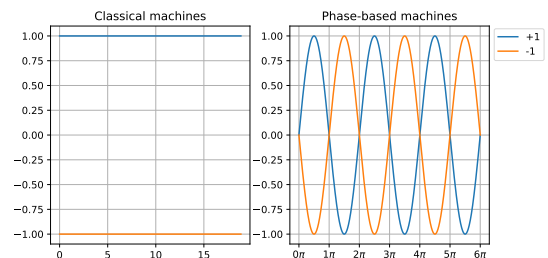


Fig. 1. Encoding of information, classically and with oscillators[5]

Since ONNs are intrinsically not meant for pattern classification, we need to rethink the structure of our model. Belyaev

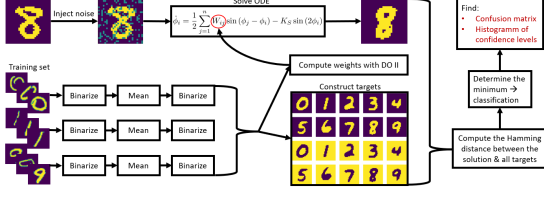


Fig. 2. Classification model of this paper

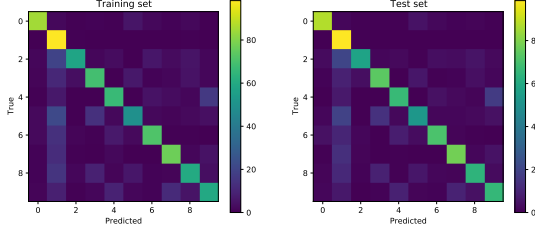


Fig. 3. Confusion matrices of the training and test set

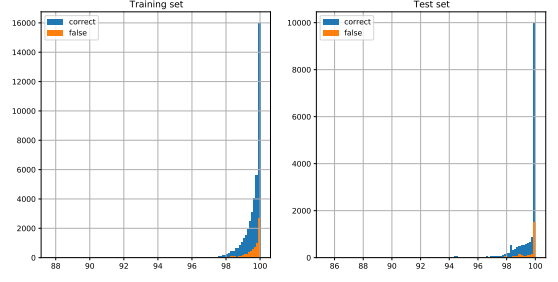


Fig. 4. Histogram of the confidence levels for the training and test set

the set out targets. These can be seen in Fig. 4 for both sets and separately for correct and false predictions therein. Generally, it can be stated that only a few pixels are spurious at the end of the computation. However, the plot also proves that the model tends to converge for all pixels to an incorrect target, as the highest bar for false predictions appears at 100%.

V. CONCLUSIONS

For the first time, we have presented ClassONN in this paper - a single layer model of fully connected coupled Kuramoto oscillators to perform image classification on the full 28x28 MNIST dataset. Using the Diederich-Opper II learning rule and subharmonic injection locking, we have achieved an accuracy of around 70% on the training and 72% on the test set.

There are various neuron models such as Kuramoto, Izhikevich [17] or van der Pol [18]. Thanks to their rich dynamics, these various models have the potential to make the phase-based paradigms more expressive. Despite the simplicity of Kuramoto's model, this paradigm shows promising results. Many questions remain unanswered ranging from an effective learning algorithm, multi-layered structure and neuron model.

Despite not having achieved the high accuracies typical for CNNs, this is the first attempt at classifying images with such a large resolution utilizing ONNs. Furthermore, it motivates to further investigate this topic, as the phase-based paradigm provides an attractive alternative to classical computing.

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IV. RESULTS

Fig. 4 presents the final relative confusion matrices for the classification of the MNIST data sets. The values along the rows sum up to 100%. Generally, one could say that the model yields identical confusion matrices. The accuracies are the following:

Training set: 69.81%

Test set: 71.88%

Now we know how successful the model is in the classification process. However, let us investigate the confidence of each classification, i.e. to which extent (in %) does the solution agree with one of the targets, to verify the model indeed converges to