Pattern Recognition with Antiferromagnet-heavy Metal Hybrid Structure

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Abstract— Nowadays, there is a great interest in artificial intelligence. One of its popular branches is deep learning, based on the neural networks consisting of artificial neurons, which are adders with a nonlinear activation function. This approach requires large amounts of training data. For example, computer vision contains different tasks of this nature, where one of the well-known problems is recognizing images of handwritten numbers. Various approaches to training convolutional neural networks on the MNIST database show less than 0.5% error. Another area of artificial intelligence is neuromorphic computing, whose goal is to build biologically plausible models of neurons in the human brain. The motivation for the approach of neuromorphic computation is that accurate modeling of biological neurons will allow solving many problems, in particular, control problems, with the same accuracy the human does.

Moreover, it opens up the possibility of creating electrical circuits that mimic the behavior of biological neurons, which will reduce energy consumption. In particular, the physical realization of neurons can be coupled oscillators that are ubiquitous in nature. The phase or frequency of the oscillators contains information that allows development of such computational schemes. In this paper, a hybrid antiferromagnetic-heavy metal structure is used to solve the problem of image recognition. During the model training the coupling coefficients of the oscillators are calculated so that pairs of oscillators corresponding to different pixel values oscillate asynchronously, and the oscillators reacting to the same value set the oscillation mode in phase. Pattern recognition error is estimated depending on the number of neurons, patterns, and signal-to-noise ratio (SNR).

1. INTRODUCTION

Nowadays the mankind show increased interest in cognitive technologies. There is a grandeur in the idea of the brain structure and operation, that makes the problem of mimicking biological behaviour of neurons and synapses not only valuable for industrial tasks but also challenging from the point of view of understanding the nature's master plan.

Most of the information that a human receives from the environment is visual. That is why the computer vision tasks, including image recognition, are so important. One of the most successful solutions for image recognition task is convolution neural network (CNN), proposed in 1989 by Yann LeCun et al., which became the foundation of computer vision [1]. Modern CNNs achieve about 99% accuracy for digit recognition task [2, 3], but it is also possible to use simpler models to classify images from MNIST [4]. Despite the high accuracy of recognition this branch of deep learning continues to develop utilizing emerging techniques, such as attention [5, 6].

The main disadvantage of deep learning methods and CNN in particular is that it is necessary to train it on the huge amount of data and spend a lot of time to optimize weight coefficients in such a way that neural network (NN) can recognize image with high accuracy [7, 8]. Moreover, there is a probability of missing sample in training set, that can lead to a dramatic consequences, since NN can't recognize images different from those it has "seen". On the contrary, neurons in the brain of a child remember different patterns without any knowledge that it is necessary to remember it and, for example, can distinguish a house from a tree without knowing of what the house is.

This is why some have turned their sights towards the physical realizations of neurons. The implementation of associative memory based on a system of oscillators is one of a wide variety of neuromorphic computation problems [9–11]. A wide range of physical phenomena and the ubiquity of oscillating systems in nature allows one to choose the types of oscillators that are most suitable for solving specific problems [12]. A significant class of oscillators is based on the oscillatory motion of spins in ferromagnetic and antiferromagnetic materials, which are attracting more and more attention of researchers [13–16]. It is especially important to study antiferromagnetic spintronic devices, since the dynamics of antiferromagnets, in spite of the great complexity in comparison with ferromagnets, opens up the possibility of creating devices operating in the terahertz frequency range [17, 18].

2. NEUROMORPHIC MODEL

The considered neuromorphic model of the antiferromagnet-heavy metal hybrid structure is described by a system of ordinary differential Equation (1)

$$\begin{cases} \dot{\varphi}_n = \eta_n, \\ \dot{\eta}_n = -\alpha\omega_{ex}\eta_n - \frac{\omega_e\omega_{ex}}{2}\sin 2\varphi_n + \sigma\omega_{ex}\left(j + A\sin(\omega_{ext}t)\right) + \omega_{ex}\sum_m k_{nm}\eta_m, \end{cases} \tag{1}$$

where φ_n is the phase of the n-th oscillator, α is the damping coefficient, ω_{ex} is the exchange frequency, ω_{an} is the anisotropy frequency, σ is the coefficient characterizing the spin transfer effect, j is the direct current density, k_{nm} is the coupling coefficient of the m-th oscillator with the n-th one. Depending on the presence or absence of an external signal of amplitude A, as well as on the ratio of the direct current density to the threshold density j_{dc}/j_{th} in the neuromorphic model, a spiking, self-oscillating, or damping mode appears. This paper deals only with the spiking mode, although it is possible to expand the study to the self-oscillating mode later.

The problem of image recognition, here it is a binary noisy 10×10 matrix, is interpreted as the problem of removing noise from the image. The neuromorphic model (1) is required to present a reference image, i.e., one of seven patterns from the training set. The neuromorphic model itself consists of $N = 100$ antiferromagnetic oscillators connected with heavy metal buses. The memorization of images by the system is carried out by calculating the coupling coefficients k_{nm} according to the Hebbian learning rule (2) [9, 19]

$$k_{nm} = \frac{1}{N}\sum_{i=1}^{p}\xi_n^i\xi_m^i, \tag{2}$$

where ξ_n^i and ξ_m^i are the n-th and m-th values of the i-th of p available in the training set image converted into a row with $n, m = \overline{0, 100}$, $\xi_n^i, \xi_m^i = \overline{0, 1}$.

The memory response to the image is the establishment of a certain oscillatory mode in the system of oscillators, which means that neurons should oscillate in phase in the case when the

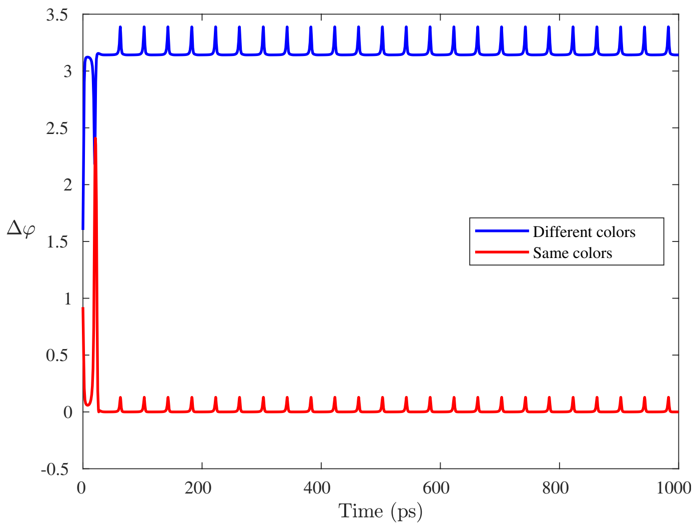


Figure 1: Oscillations around the positions $\Delta\varphi = \pi$ for neurons representing different colors and $\Delta\varphi = 0$ for neurons representing the same colors.

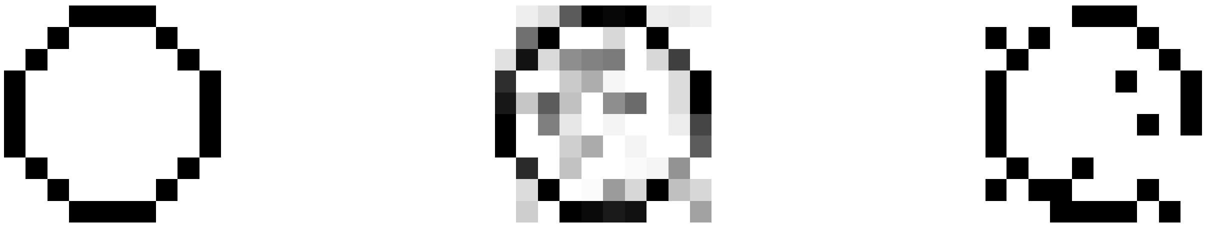
input data are represented by the same colors, and anti phase in another case, as demonstrated in Fig. 1. The input data are the initial conditions imposed on φ, which take on the values 0 and π, depending on the color of the pixel. The initial conditions for η are zero.

3. RESULTS

The output image is a correlation matrix of resulting φ_1 and φ_n. Its values, which are 0 and 1, depends on the sign of $\sin\varphi_1 \cdot \sin\varphi_m$ value. For instance, Fig. 2 demonstrates image in the training set (a), noised input image with SNR = 1 (b), and recognized one (c). The Hamming distance (3)

$$D^i = \sum_{n=1}^{100} \left| \xi_n^i - \tilde{\xi}_n^i \right| \tag{3}$$

between converted to row image ξ_n^i from training set and recognized $\tilde{\xi}_n^i = \sin\varphi_1^i \cdot \sin\varphi_n^i$ equals 10, therefore $D^i \in [0, 100]$.



(a) (b) (c)

Figure 2: Training, input and recognized pattern "zero".

Figure 3 demonstrates dependence of general average error $D = \left(\sum_j^k \sum_i^p D_j^i \right) / (kp)$ and average error for only one (first) pattern "cross" $D^1 = \frac{1}{k} \sum_j^k D_j^1$ on SNR for different amount of patterns p in the training set and number of iterations $k = 20$. In most cases, the lower SNR (the more noise in the image), the higher the Hamming distance, however there is no clear dependence. There was one more experiment on finding dependence of D and D^i on p. Obtained results are presented in Fig. 4. Based on the results, one can say that for the selected images, the number of patterns to be recognized does not lead to an increase or decrease in the error in a linear manner. The question of the influence of the pattern added to the training set itself remains open.

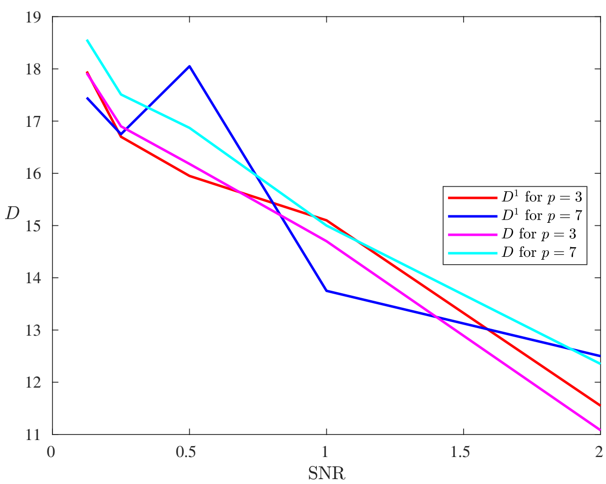


Figure 3: Dependence of the error on SNR.

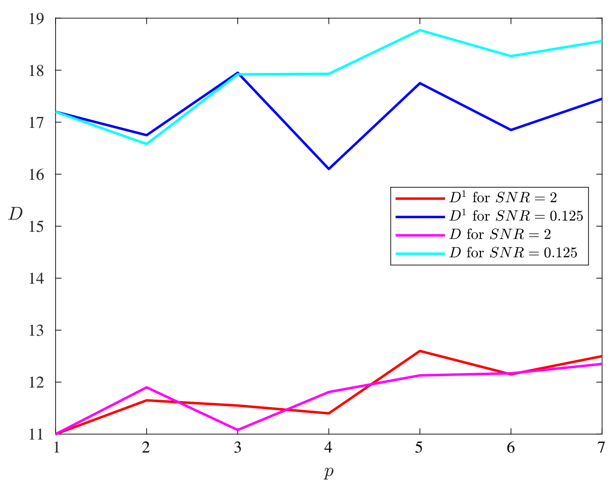


Figure 4: Dependence of the error on p.

4. CONCLUSION

This work presents implementation of associative memory with antiferromagnet-heavy metal structure in spiking mode. It is applied to recognize patterns, which are binary 10×10 images. The model consists of 100 antiferromagnet oscillators, connected with each other with heavy-metal busses. To calculate weight coefficients one can use Hebbian learning rule, but it is also possible to consider other rules or optimization methods to find appropriate coefficients.

Input data are the initial conditions for φ_n in (1), which are $0 + \varepsilon$ and $\pi + \varepsilon$, where ε is a value of white Gaussian noise. The use of other parameters of the model as input remains a question, as well as the use of the model in a self-oscillating mode and the difference in pattern recognition in both of these cases. Memory response here is synchronization of oscillators in phase or anti phase, depending on the difference between colors of pixels corresponding to these neurons. it is also necessary to synchronize not only the phases, but also the spikes.

There is no linear dependence of Hamming distance between recognized and reference image on SNR or size of training set. For a better understanding of recognition, it is necessary to investigate the dependence of the error on other types of noise. One should also study the question of the influence of specific patterns on the recognition error.

The future work should also include the processing of color images, but at the same time it is worth remembering that nowadays there are image recognition methods that work much better than the methods of neuromorphic computations, and such tasks should be considered solely as auxiliary for a better understanding of the scheme under study itself. In the future, the knowledge about the system obtained in this way can be applied for more suitable for neuromorphic computations problems of time sequences recognition.

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