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Time-delay encoded image recognition in a network of resistively-coupled VO₂ on Si oscillators

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Abstract— Oscillatory neural networks based on insulator to metal transition of VO₂ switches are implemented for image recognition. The VO₂ oscillators are fabricated on silicon in a CMOS compatible process. A fully-connected network of coupled oscillators is investigated using programmable resistors as coupling elements. In this approach, input of the image information and data processing is performed in the time domain. In particular, tuning the coupling resistors allows to control the phase-relation between the oscillators. This is used to memorize and recognize patterns in an analog circuit. The concept is demonstrated experimentally on a three-VO₂ oscillator network, network whereas simulations are performed on a larger 9-oscillators circuit.

Index Terms— associative memory, Oscillatory Neural Networks, phase change, relaxation oscillators, VO₂

I. INTRODUCTION

COMPLEX and unstructured problems like speech or image recognition are currently solved most effectively by deep learning algorithms running on specialized electronic circuits such as graphical processing units (GPUs) [1]. However, the extensive computation effort on traditional digital architectures requires massive computing resources. Therefore, alternative, brain-inspired hardware solutions are being researched to enhance machine learning techniques based on neural networks through increased performance and reduced power consumption [2,3]. Common approaches to such neuromorphic hardware are based on artificial neural networks [4-8] that use the amplitude of the voltage or current to encode information.

As an alternative approach, the oscillatory neural network (ONN) draws upon the physical phenomena of synchronization of oscillators which contain associative memory capabilities [9-12]. Bringing the information in the phase relations of the oscillators, this technology offers the advantage of being resilient to scaled power supply. As the amplitude of the signal is not used to carry information, it can be chosen to optimize power consumption and noise. Due to the advances in the nanoscale technology research, different implementations of compact, CMOS compatible oscillators have been presented [13-18]. VO₂ based oscillators represent one of the most

promising technology, due to their compact design and high scalability compared to standard CMOS oscillators and low power operation compared to other oscillator technologies [19-22]. As a further advantage, it has been demonstrated that VO₂ oscillators can be easily coupled using capacitive or resistive elements [23-25]. Previous works show simulations of small networks of VO₂ coupled oscillators with computing capabilities [24-27].

In this work an experimental demonstration of an image recognition system based on VO₂ is presented. The designed system stores the training images in the coupling weights of the oscillators and uses time-encoding of the digital information. The image to be recognized is encoded in the time delays of the oscillator's inputs, and the output is read as phase difference of the oscillator waveforms. Information encoding in the time domain does not suffer from scaled power supplies, representing an advantage for the future integrated technology nodes. The concept is validated experimentally on a network of three coupled oscillators. The devices oscillate with amplitudes in the 100 mV range when biased with 1V V_{DD} and consume about 20 μ W power. Simulations show an extension of this concept for a 3x3 image filter computation unit, which is compatible with analog filters for feature maps functions in Convolutional Neural Networks [29-34].

II. CONCEPT DESCRIPTION

Figure 1 shows the circuit diagram of the network of fully resistively-coupled VO₂ oscillators. A single oscillator unit consists of a VO₂ resistor and a biasing transistor as load. The input of the network is the voltage supply of each oscillator, while the oscillating output signal is obtained at the drain of the biasing transistor. Tunable resistances are used as coupling elements and serve as the ONN memory. A gray-scale input image is encoded in the delay of the switching of the V_{DD} of each oscillator compared to the reference input unit. The oscillatory network requires around 10 oscillating periods to stabilize, before reading a constant phase relation. The output image is encoded in the phase difference between the oscillators and the reference. With a standard time-to-digital conversion technique [35], the relative output is read and translated in digital information.

Representing a grey-scale image, an oscillator in phase with the reference will be read as white pixel, an oscillator in out-of-phase with the reference is read as black pixel (represented in Figure 1 as digital 1 or 0 information as an illustrative example). The ONNs are trained with a fast learning technique using the Hebbian Learning Rule (HLR) for ONN, described in [9]. Following the HLR, values between 1 and -1 are assigned to the pixels of each training image, with respect to the gray-scale value of each pixel; the coupling weight C_{ij} between the oscillators are then calculated with the simple relation:

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Fig. 1. Circuit scheme of a VO₂ oscillator network. The input of the network is the time-delayed voltage supply and the oscillator waveform is measured on the drain of the biasing transistor. A gray scale image is flattened, and each pixel is encoded in a temporal delay in the switching of one oscillator. In particular, a white pixel is translated in an input delay of 0 with respect to a reference signal, and a black pixel is translated in an input delay of $T/2$, where T is the period of the oscillations. The output is a phase difference in the oscillators, which is converted back into digital bits. The resistive coupling matrix represent the memory of the circuit, trained with the Hebbian Learning Rule for ONNs.

$$C_{ij} = \frac{1}{n} \sum_{k=0}^m \vartheta_i^k \overline{\vartheta_j^k} \quad (1)$$

where ϑ^k is the value assigned to pixel i of the training image k , m is the number of trained images and n the number of pixels per image. The weights C_{ij} are then translated in circuit values of the coupling resistances R_{ij} . Following this design, an Oscillatory Neural Network system in which the information is encoded in the timing of the signal is realized. This system allows to exploit the associative memory capabilities of ONNs to realize tasks as image recognition, and doesn't rely on amplitude thresholding functions, holding the promise of not suffering from scaled-supply voltages. Further, as the same amplitude is used for all grey-scale values from black to white, the relative noise of each pixel is independent of the information carried and biased data processing is avoided.

III. RESULTS

Device fabrication- The VO₂ devices are realized on a 4'' Si wafer on top of 1 μm thermal SiO₂ layer, as described in more detail in [36]. A 50 nm VO₂ layer was deposited, etched into stripes with dry-etching and contacted with Ni/Au (Fig. 2). Minimum device dimension of the VO₂ area were 0.2 x 1 μm^2 . Though operation in ambient atmosphere is possible, the devices were tested in vacuum using a temperature-controlled probestation. All electrical connections were provided through discrete external components. In Figure 2 the typical waveform for a VO₂ oscillator is depicted. Highly scaled devices show oscillations amplitudes around 0.5 V with power supply scaled down to 1 V, and low power consumption ($\sim 20 \mu\text{W}$).

Fig. 2: Left: Scanning Electron Microscopy image of a VO₂ element (0.7 x 1 μm). Right: Single oscillator output. The device shows oscillation below 0.5 V with a power supply of 1 V, and power consumption of 20 μW . The power consumption is calculated as $V_{DD} \cdot I_{VO2}$, where I_{VO2} is the value of the current that flows through the VO₂ resistor averaged across the oscillating period.

These figures of merit are competitive when compared to other oscillator technologies [19-22]. Experiments show reliable oscillations of the device up to 10^9 oscillating periods, in vacuum and in ambient conditions. However, device-to-device variability of resistances and threshold voltages range between 10 and 20%, currently posing the main limitation to couple more than 3 devices. The highest operation temperature is limited to the metal-to-insulator transition, that occurs at 330 K, but demonstrations of Ge-doped VO₂ films show that this limit can be increased with material engineering [37].

Image recognition experiments - The image recognition through the oscillators associative memory is demonstrated on resistive-coupled oscillator network consisting of three VO₂ oscillators. Resistive-coupling, compared to capacitive-coupling, is explored with the technological vision of future implementation of the coupling resistances with memristive technology. This in fact would allow for the reconfigurability of the circuit. Fig. 3a shows the schematic of the experimental setup. Three oscillators are coupled in frequency with R-C elements. The relative phase among the oscillators can be modified upon tuning of the individual coupling resistances, representing the weights, i.e. the memory of the system. Two 3-pixel images are memorized in these resistances' weights, which are computed using HLR (Figure 3b). From equation (1), the normalized weights for memorizing the selected patterns in Figure 3b are calculated as $C_{12} = 1$, $C_{13,23} = 0$, and are translated in the values of coupling resistances $R_{12} = 300 \text{ k}\Omega$, $R_{13,23} = 680 \text{ k}\Omega$. The test patterns were encoded in the time delay of the oscillators input. For the experiments, we kept the input of oscillators 1 and 3 at a fixed time delay $\Delta t = 225 \mu\text{s}$, corresponding to $\Delta t = T/2$, where T is the oscillation period (around 450 μs). We performed a sweep of the time delay of the oscillator 2 between 0 and $T/2$. The variation in time delay of an oscillator represents the varying gray values of a pixel which need to be recognized as either black or white depending on the memorized patterns.

In Figure 3c we show the waveforms for two experiments, corresponding to two different initial time delays of oscillator 2. Depending whether Δt is closer to 0 or $T/2$, the output phase of oscillator stabilizes at 0 (top graph) or $T/2$ (bottom graph). Hence, the 3 oscillators fall into one of the trained patterns 1 or 2 therefore recognizing successfully the two images encoded in the circuit. In Figure 3d the output phase of the three oscillators is depicted for the full range of input delays of oscillator 2. As noise is present in the circuit, wrong recognition is sometimes

Fig. 3. a) Schematic representation of the experimental setup for a VO₂ coupled oscillators image recognition experiment. Three oscillators are coupled through RC elements consisting of a capacitance $C = 1$ pF and tunable resistances, that represent the memory of the network ($R_{12} = 300$ k Ω , $R_{13,23} = 680$ k Ω). b) Trained and test network of the 3-VO₂ ONN. c) Experimental results of successful pattern recognition. The input delay of Oscillator 1 and 3 is kept fixed. By varying the input delay of oscillator 2, the two stored images are correctly recognized. d) Experimental results of the image recognition with 3-VO₂ oscillators. For small and large delays of Input 2, respectively the first and second stored image are correctly recognized. Intermediate delays result in recognition of an erroneous image.

obtained. Each experiment was therefore conducted multiple times. Figure 3d shows the output phase, calculated after a stabilization period of around 10 oscillations, and averaged over multiple experiments; the error bars correspond to the standard deviation of the output phases. Two regions of successful recognition are identified, when the deviation from the trained pattern and the test pattern is below 20%. For intermediate time delays, the output phase stabilizes to an erroneous pattern.

Simulations - SPICE circuit simulations have been performed to study the image recognition performances of a 9-pixels ONN, implementing an equivalent circuit model of the VO₂ device as described in [28]. The size of the network was chosen to comply with the smaller image filter unit commonly used for Convolutional Neural Networks [31]. Six images were selected for training (Fig 4a). The values of the coupling

resistances between the oscillators were calculated with HLR. Aiming for recognition of pattern 2 we fixed the input delay of six oscillators and changed the delay of the remaining three between 0 and $T/2$, as in the experiments. Three regions were identified (Figure 4b): for small delays, Image 1 was recognized, for large delays, Image 2 was recognized. In between, the oscillators stabilize in a configuration that is different from the memorized ones. In this region the difference between the test image and the trained image is higher than 20%, and the network fails in the recognition.

To explore the limits of the HLR applied to VO₂ ONN, mathematical simulations were performed. Aiming at the recognition of pattern 2, test patterns with increasing grey-scale deviations were input to the network starting from coupling parameters calculated with HLR. Similar to the experiments in Figure 3, we find that the ONN outputs the correct image up to 25% of deviation of the test pattern from the memorized pattern (Fig 4c). Further, simulations show that the ONN can tolerate up to 5% variability of the VO₂ parameters (insulating and metallic resistance).

IV. CONCLUSION

We experimentally demonstrate an image recognition computation performed by a 3-VO₂ Oscillatory Neural Network fabricated on a Si platform, with time-encoded signal input and output. The experiments show that with a 3-VO₂ coupled oscillator system it is possible to store different oscillating phase configuration and to influence the output phase relations of the oscillators with time-delayed encoded input. The learning performance for the VO₂-ONN trained with Hebbian Learning Rule was addressed with simulation on 9-pixel computation system, showing that the network trained with HLR is effective in recognizing simple patterns with up to 25% noise deviation compared to the memorized pattern. This work is the first step towards building larger analog computation units that can be used as filters in Convolutional Neural Networks.

Fig. 4: a) trained and test pattern; b) Results of the Spice circuit simulation on a 9-VO₂ ONN trained with HLR. For small and large delays of Input 3,6,9, respectively the first and third stored patterns are recognized. Intermediate delays result in recognition of an erroneous pattern; c) statistics on the recognition success with an input that is increasingly different from the trained pattern. We refer to the difference between the test and trained pattern in terms of gray-scale deviation of the test image from the original image. The recognition is accurate up to 25% of deviation between test and trained pattern.

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