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Research paper

Experimental study of $LiNbO_3$ memristors for use in neuromorphic computing

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ABSTRACT

This paper describes the fabrication and characterization of Lithium Niobate ($LiNbO_3$) memristor devices that have the ability to be tuned to a specific resistance state within a continuous resistance range. This is essential for programming neuromorphic systems based on memristor crossbars in order to achieve best deep learning capability. The memristor devices were formed using a 42 nm layer of $LiNbO_3$ sandwiched between two metal electrodes. I-V curves demonstrate a typical and repeatable memristor characteristic from −3 V to 3 V. Such devices have a continuous resistance range that has a maximum to minimum resistance ratio of about 100, and the ability to program intermediate resistance states. The results also show the ability to read the device symmetrically with a positive or negative voltage, and strong data retention after the programming phase.

1. Introduction

Memristors [1] have received significant attention since first real memristor was found in 2008 [2]. Due to the structural simplicity and scalability, memristors have a great potential to revolutionize future applications such as random access memory and neuromorphic computing. Memristors can provide low power needed by these applications and therefore expand computing capability for future computing systems. Since then, a lot of progress has been made in research of resistive random access memory (RRAM). Recently more research effort has focused on using memristor as a building block to construct neuromorphic systems [3–5]. Physical memristors [6] can be laid out in a high density grid known as a crossbar [7]. Using a crossbar arrangement, memristors have the potential to be fabricated with an areal density greater than that of synapses within brain tissue [5]. These devices can be used to produce high density, extreme low-power, neuromorphic hardware capable of performing many parallel multiply-add operations in the analog domain [3,8]. Neuromorphic systems based on memristor crossbars have potential to perform at a power efficiency of 6 to 8 orders of magnitude greater than that of traditional RISC processors [9].

One of the limitations of these systems is the current state of memristor technology. As memristors for non-volatile memory systems [10] have matured, the technology has forced the development of a memristor [12] that can switch its entire resistance range as quickly and reliably as possible to allow fast memory access [11–13]. However, the ideal memristor in neuromorphic computing systems should have multiple accessible resistance levels that allow for a programmable analog resistance range [3,14]. Among previously researched materials, TiO_x [2], silver nanoparticles in a-Si [12], $LiCoO_x$ [15], and $LiNbO_3$ are potential candidates for neuromorphic computing applications.

As a continuing effort in developing memristive devices suitable for neuromorphic computing, this paper presents Lithium Niobate ($LiNbO_3$) memristors. These devices show a multistate resolution that is essential for programming neuromorphic systems based on memristor crossbars.

2. Necessity of tunability from memristors

A common approach for the development of memristor-based neuromorphic circuits is to store each synaptic value on a single memristor in analog form as a resistance value [3,16]. This requires the use of a continuous resistance range in a memristor to store the weight matrix produced by a learning algorithm. More specifically, these devices will be used in systems [3] that implement supervised learning algorithms such as single and multilayer perceptrons. In this case it is important to be able to iteratively program a target resistance through a number of feedback controlled voltage pulses [3] as opposed to abruptly switching the device between two binary states.

Memristor based perceptron circuits work in two different modes of operation. First the memristors are trained, or programmed to specific resistance values according to an input training dataset. Once the resistance values are optimized by the learning algorithm, the system will operate in an evaluation mode. When in the evaluation mode,

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Table 1
Minimum pulse width required to induce a partial state change to a memristor device based on memristor switching time and the voltage of the applied pulse.

Approx. switching time	Switching voltage (V)	Minimum pulse width required
10 ns	6	1 ps
10 ns	4.5	10 ps
100 ns	4.5	100 ps
1 μs	4.5	1 ns
10 μs	4.5	10 ns

resistance values should not change, and memristor switching dynamics are much less (if at all) relevant.

Using fast memristor memory devices in perceptrons is difficult because tuning to a specific resistance will require unrealistically small voltage pulses. Table 1 [14] shows that if the entire resistance range of a device can be switched in 10 ns, then 10 ps pulses are required to attain the definition needed to successfully program a neuromorphic crossbar. It should be noted that the switching speed of a memristor device will not impact how quickly the system can evaluate a given problem, only how long it takes to get memristors into a specific resistance state during training. In these systems the memristors will typically be trained once before they are used extensively in an evaluation mode.

To summarize, the ideal memristor device for our application would have a number of accessible resistance states within its continuous resistance range, and it should have a symmetric region where a range of positive and negative voltages can be applied during evaluation without changes the resistance. Lastly, the programmed resistance should be retained for a long period of time. In this paper, the presented $LiNbO_3$ memristors are studied experimentally for these specific requirements by neuromorphic computing. Our results show a large programmable continuous resistance range, the ability to symmetrically read the devices, and strong data retention.

3. Device fabrication and characterization

The memristor device structure (from bottom: $Ti/Pt/LiNbO_3/Ti/Pt$) proposed in this work is based on a 42 nm $LiNbO_3$ switching layer prepared with pulsed laser deposition (PLD) using the method proposed in [17,18]. The bottom electrode consists of 10 nm titanium and 50 nm platinum and the top electrode consists of 10 nm titanium and 80 nm platinum. The substrate is silicon topped with 2 μm of plasma enhanced chemical vapor deposition (PECVD) silicon dioxide. Fig. 1 shows the XRD image of the produced $LiNbO_3$ thin film for the memristor device

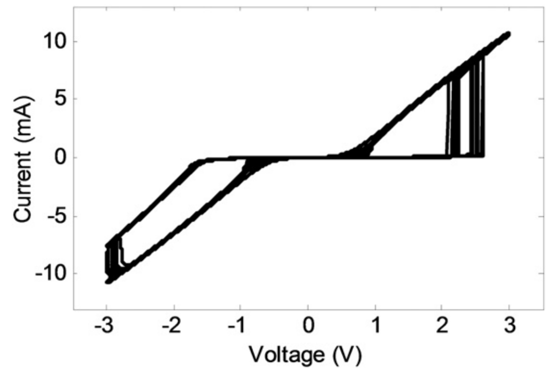

Fig. 2. I-V characteristic of a 15 μm^2 $LiNiO_3$ device. The many hysteresis loops show strong repeatability with a small amount of variation in the positive write voltage threshold.

described in this paper. The image shows the existence of only $LiNbO_3$ peaks (dark bands) which are (012), (104), (006) and (116). Titanium is a kind of active metal similar with Ag and Cu. The titanium top electrode possibly generates the motion of oxygen vacancies inside the film to help further enable memristive characteristics. In this study, devices are fabricated using optical lithography, therefore device sizes range from 2.5 μm^2 to 400 μm^2 with overlap shapes as either rectangular or circular. The results shown in this paper are from 15 μm^2 devices.

The memristors were measured using a cyclic voltammetry setup at room temperature with a computer controlled Keithley 2400 source meter. In general, a forming process is necessary for each device. This is performed by pulsing the memristor at voltages between 3 V and 4 V. After that, a typical and consistent memristive characteristic can be seen in the I-V sweep for a 15 μm^2 device. Fig. 2 shows the repeatability of the hysteresis loop in a device where several successive loops are reliably performed. From the results, this memristor exhibits bipolar resistive switching. The positive and negative write threshold voltages for this device are about 2.4 V and −2.8 V respectively. Although, a small amount variation is present in the switching voltage threshold between loops (see Fig. 3). Assuming a read voltage of 1.5 V, the R_{MAX}/R_{MIN} ratio of these devices is about 100 ($R_{MIN} = 360\,\Omega$ and $R_{MAX} = 35\,k\Omega$). The average resistance of these devices is a little lower than desired, but it is likely that the resistance of these devices will be reduced if they are patterned with feature sizes in the nanoscale. Work in [10] shows a similar effect when reducing device area, and we plan to verify that this trend will be present in our devices as future work.

As addressed earlier, compared to flash memory applications, being able to achieve stable intermediate states is critical in neuromorphic

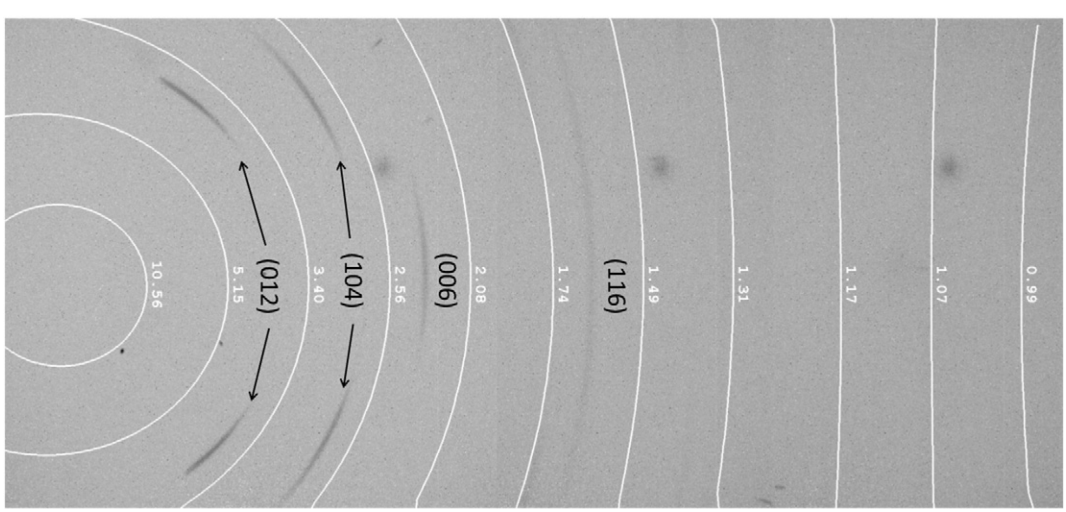

Fig. 1. X-ray diffraction (XRD) image of $LiNbO_3$ thin film.