192
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Towards Fast and Direct Memory Read-out by Multi-beam Scanning Electron Microscopy and Deep Learning Image Classification

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Program execution code and data is often stored in non-volatile memory inside embedded devices. Information extraction from such memory is required for software debugging and hardware failure analysis. Beyond this, data retrieval is needed in chip reverse engineering where patent violations are analyzed or for forensic purposes where critical information needs to be recovered.

EEPROM (Electrically Erasable Programmable Read-Only Memory) is one type of non-volatile memory which is widely used in microcontrollers and computers. This kind of memory consists of arrays of memory transistors which can be set to two different states. Either electrically charged or uncharged, they represent the two values of a binary digit – a bit (1/0). Imaged by a scanning electron microscope, electrically charged and not-charged transistors generate different image signals, based on passive voltage contrast [1]. This contrast mechanism was previously described as a valid tactic to image memory content from an EEPROM by single beam SEM [2].

In this study, semi-automated image analysis based on a deep learning neural network approach is applied in combination with high-throughput, multi-beam scanning electron microscopy to establish an advanced method for reading out memory cells reliably at a large scale.

An off-the-shelf EEPROM chip was in a first step programmed with an alternating, regular "0/1" bit pattern and then de-processed by a delayering backside approach [2]. Silicon substrate was gradually removed by polishing and wet etching until the tunnel oxide layer of the floating gate transistors was exposed. Images were acquired using a 61-beam scanning electron microscope, the ZEISS MultiSEM 505 [3], operated under low-dose conditions, see figure 1a). Probe current was set to 20 pA per beam at 2.5 keV landing energy, pixel size was 15 nm and pixel dwell time was 100 ns, while the image acquisition time was 12.5 s for a total scan area of 7.13e+04 µm². It was determined that at this, sub-critical, electron dose level the memory transistor charges were not affected. We found that only a fraction of images was useful for further image analysis due to charge accumulation of non-conducting regions. Sub-frames of charged and uncharged memory cells (n=150, each) were interactively selected, and aligned to a common average by an iterative 2D alignment procedure [4], see figure 1b). Two randomly defined subsets (n=50, each) of aligned sub-images were used as ground truth to train a deep learning neural network for image classification [5, 6], see figure 1c). Identification accuracy of the two image sub-populations by the neural network was found to be 95.2 % ±1.8 % (average values of n=1000 runs). Two class average images of identified cell image populations (n=100, each) were calculated, see figure 1d). One class average clearly shows a bright region inside the memory cell center (figure 1d), bottom) based on passive voltage contrast resulting from electrical charges. The second class average shows no signal in the cell center (figure 1d), top), thus no charge is present. After assigning the identified contrast differences to binary bit values 0/1 (figure 1e)) and after re-mapping these values back to the original image positions (figure 1f)) we were able to confirm the initially programmed, alternating bit pattern on the EEPROM with a high fidelity.

With this feasibility study, we demonstrated that deep learning based image classification can be used to analyze low-dose, multi-beam scanning electron micrographs in a semi-automated way. Classification of memory cells was successfully carried out by the neural network and it was possible to find back the original pre-programmed regular bit pattern on the EEPROM. An essential next step towards a routine use of this workflow for large areas is to improve the conductivity of the sample which can be done by e.g. applying a thin (5 – 10 nm) carbon layer to the surface. Automated position detection can be carried out by image template matching procedures and fidelity of image classification would greatly benefit from increasing the number of sub-images used as ground truth for network training. By combining all these improvements, fully automated, high-throughput read-out of memory content will be in reach.

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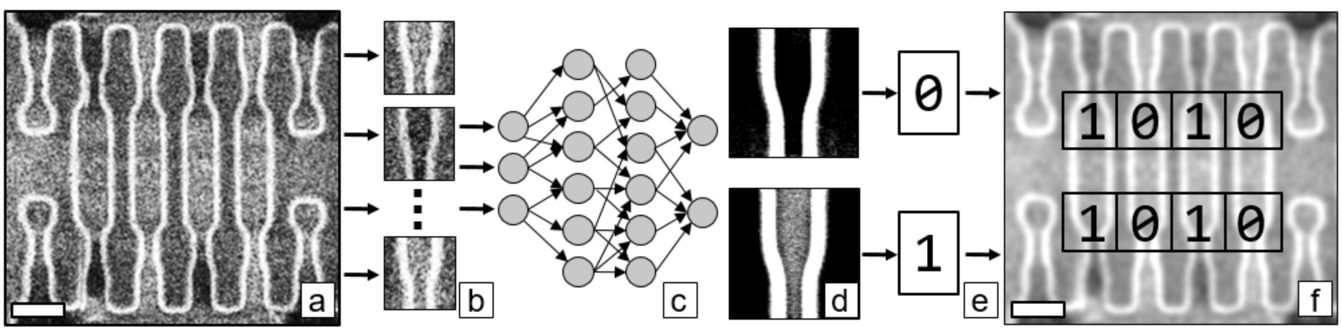

Figure 1. Readout of memory cells a) EEPROM chip imaged by a multi-beam SEM under low-dose conditions (scale bar equals 2 µm) b) selected sub-frames of memory cells (n=300) were visually identified and registered iteratively. Two subsets (n=50, each) were used as ground truth to c) train a deep learning neural network for image classification. Identification accuracy of charged and un-charged memory cells relative to the pre-programmed bit pattern was found to be 95.2 % ±1.8 % d) two class averages of identified cell image populations (n=100, each); one class average (bottom) shows passive voltage contrast resulting from electrical charges in the memory cell center e) assignment of sub-frames found in (d) to binary (0/1) memory bit values f) re-mapping of identified bits to original multi-beam SEM image.

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