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Impact of Cyber-Physical Systems on Research and Development of Semiconductor Devices

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1. Introduction

In the industrial field of semiconductors, process innovations are crucial for fabricating high-performance semiconductor devices. For example, the crystallization of amorphous silicon thin films by excimer laser annealing (ELA) enables high-performance smartphones in the display industry. Accomplishing these process innovations in the semiconductor field is vital for realizing Society 5.0 (Society 5.0: Japan aims to achieve economic development and provide solutions to social issues through cyber-physical systems (CPSs)).

The recent progress in CPSs, which connect semiconductor manufacturing systems, paves the way for accelerating the development of innovative semiconductor devices.

To improve the acceleration of R&D by CPSs, it is important to develop semiconductor manufacturing systems for novel semiconductor device processes using CPSs such as deep learning. In this paper, we report on estimating the device characteristics of low-temperature polycrystalline silicon thin-film transistors (LTPS-TFTs) through deep learning.

TFTs are used as switching and driving elements in display devices. LTPS-TFTs have attracted attention because of their low process temperature (~400 °C) and high carrier mobility (~100 cm^2/Vs). A polysilicon film was formed by the ELA process. In the ELA process, the a-Si film melted, and the molten Si then began to cool and solidify as crystals, leading to alterations in the morphology of the Si film, such as the surface color and surface roughness. These surface changes correlate with the characteristics of the polysilicon films. The quality of the crystallized polysilicon Si was evaluated using optical inspection methods. Therefore, we attempted to quantitatively predict the mobility and gate threshold voltage (V_{th}) of the LTPS-TFT using deep learning from optical microscope images of the polysilicon film.

Before performing deep learning, we acquired microscope images of a polysilicon film and field effect mobility and V_{th} as a dataset through the LTPS-TFT fabrication process. First, an a-Si film was deposited via LPCVD on a glass substrate. We then used the ELA method with various fluences to form polysilicon films. In addition, ELA with a laser intensity distribution was performed using optical masks to control the grain size of the grown crystal. After ELA, an optical microscope was used to capture the images of the laser-annealed polysilicon film. Subsequently, the TFT was fabricated using a conventional top-gate TFT fabrication process, the current-voltage characteristics were measured, and the field-effect mobility and Vth were calculated. With this dataset, we performed deep learning using pre-trained VGG16, a deep convolutional neural network (CNN), to classify images. During the training of the deep learning model, weight parameters were updated to reduce the mean square error (MSE) between the actual measured value and the predicted value (CNN output).

2. Methodology

2.1 TFT Fabrication

The n-channel LTPS TFT is fabricated as follows. First, a-Si (100 nm) films were deposited onto a quartz substrate via low-pressure chemical vapor deposition (CVD) at 550 °C. Subsequently, the a-Si films were crystallized using ELA. After the poly-crystallization of the Si films, poly-Si films were defined by creating island patterns using photolithography and wet etching with a mixture of HF, HNO_3, and H_2O. A gate insulator SiO_2 (100 nm) film was deposited at 350 °C using microwave-excited plasma-enhanced CVD. The gate electrode was fabricated by depositing a TiN (150 nm) film using reactive DC magnetron sputtering and patterned by wet etching (a mixture of HF, HNO^3, and H^2O). P+ ions at 140 keV with a dose of 5×10^{15} cm^{-2} were implanted to form a self-aligned source/drain region, utilizing the gate electrode pattern as a mask, followed by activation annealing in N_2 ambient at 550 °C for 1 h. Next, a dielectric film of SiO_2 (150 nm) was deposited by employing atmospheric pressure CVD at 400 °C. The contact holes were opened by wet etching (HF solution).

A metallic Al contact was deposited using DC magnetron sputtering and patterned by wet etching (a mixture of H_3PO_4, CH_3COOH, HNO_3, and H_2O). Finally, the TFT was annealed at 400 °C for 0.5 h under the forming gas (Ar/H_2 = 900/100 sccm). In this study, the length (L) and width (W) of the fabricated TFT
channels were 20 μm and 30 μm, respectively.

2.2 Deep learning

A convolutional neural network (CNN), which accepts optical microscope images as input and produces mobility as the output, was used to estimate the mobility from the image. Optical microscope images were cropped, with the image of the area between the source and drain used as the input image, as shown in Figure 1. Ninety percent of the data was used as training data to train the network, with the remaining 10% used for validation purposes. The CNN was trained to minimize the mean squared error (MSE) using an ADAM optimizer [1]. To qualitatively understand which part of the image the CNN focuses on to estimate mobility, gradient-weighted class activation mapping (Grad-CAM) [2] was applied to the deepest layer of the CNN designed to solve the classification problem based on the magnitude of mobility. However, Grad-CAM is a system that can be used for classification problems but cannot be applied to regression problems.

We developed gradient-weighted regression activation mapping (Grad-RAM) to determine which part of the image is the CNN in regression problems [3].

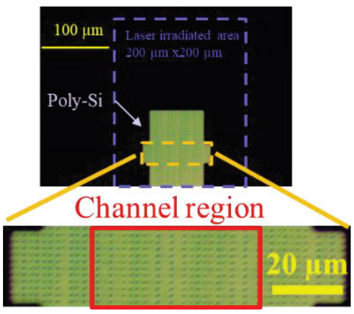

Fig. 1 Optical microscope image and cropped image of the input data

In this experiment, an a-Si substrate with a film thickness of 100 nm was polycrystalline using a KrF excimer laser (wavelength of 248 nm). The laser fluence varied from 450 to 700 mJ/cm^2. LTPS thin films were crystallized using intensity-controlled ELA, as reported in our previous study [4]. In this experiment, uniform square-shaped grains in the size range of 1–2.5 μm were formed at the optimized laser fluence. Optical microscopy images, as shown in Figure 2, were obtained from the LTPS prepared under various conditions. Subsequently, a thin-film transistor (TFT) device was manufactured. The field-effect mobility was calculated by measuring the current-voltage characteristics of the TFT devices. Deep learning was performed using LTPS images and field-effect mobility/threshold voltage datasets (480 sets). We performed deep learning using pre-trained VGG16, a convolutional neural network (CNN) architecture. During the training of the deep learning model, the weight parameters were updated to reduce the mean square error (MSE) between the actual measured value and the predicted value (CNN output).

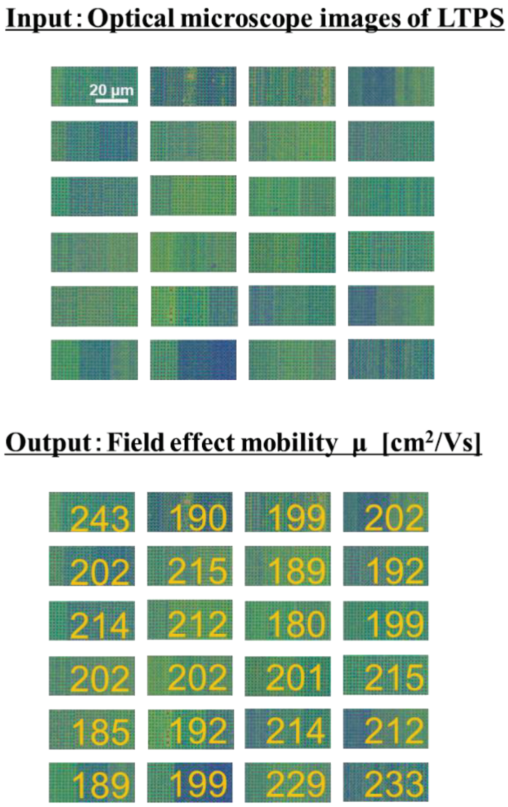

Fig. 2 Input data of optical microscope images and output data of field effect mobilities for deep learning.

3. Results and discussion

Figure 3 shows the relationship between the grain size and mobility of the LTPS-TFTs. For a projected dot interval of 1.0−2.5 μm, the actual grain size was the same as that of the projected dot interval.

At dot array pitches of 3 μm and 4 μm, the variation in the formed grain size was significantly large; therefore, the variation in the field-effect mobility was also significant, consistent with the prediction of previous studies that the variation in mobility increases as the variation in grain size increases [5].

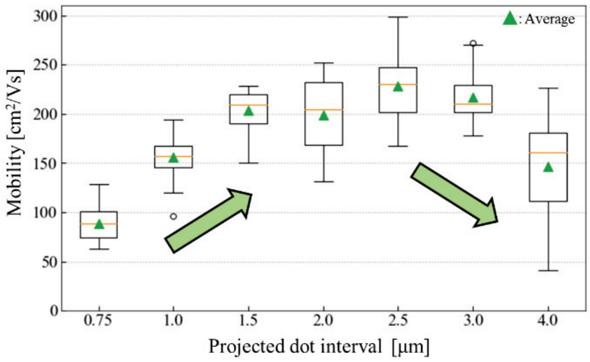

Fig. 3 Experimental data of the field effect mobilities for various projected dot intervals.

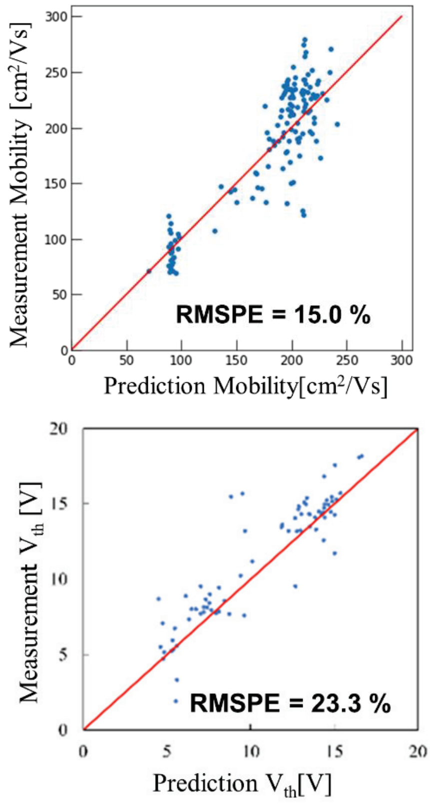

Fig..4 Predicted mobilities and Vth of LTPS-TFTs for validation data. (CNN: pre-trained VGG16)

At a projected dot interval of 0.75 μm, the actual grain sizes were of different sizes, possibly due to the resolution of the lens.

Figure 4 shows the relationship between measured and prediction values (CNN output). Regarding mobility, its root mean square percentage error (RMSPE) was 15.0 %. In contrast, for Vth, its RMSPE was 23.3 %. From Figure 4 and microscope images, it was confirmed that TFT characteristics were predicted with the information of the grain size and position in the optical microscope images, and CNN extracted their features in the images during training.

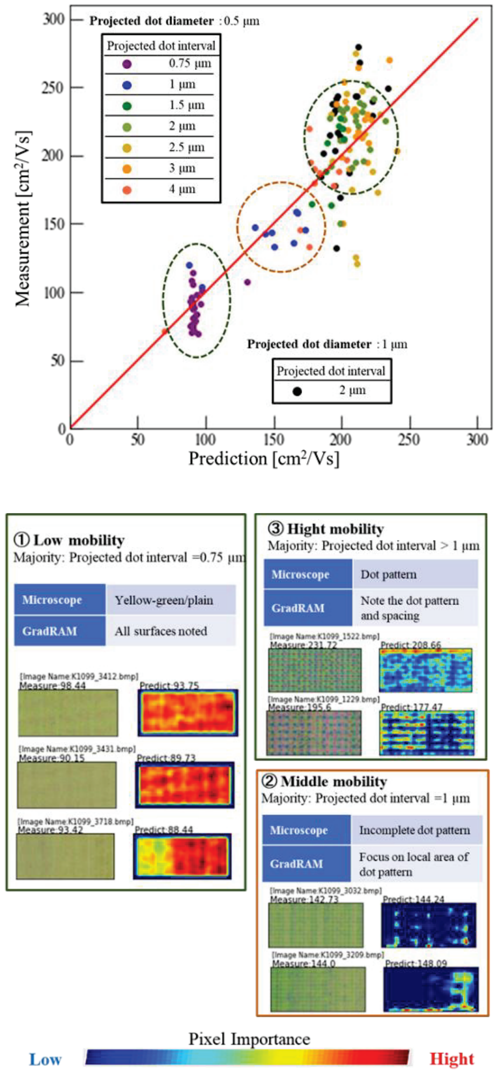

Fig. 5 GRAD-RAM images at various field effect mobilities.

Figure 5 shows the GRAD-RAM images at various field-effect mobilities and the optical microscopy images corresponding to the respective GRAD-RAM images. In addition, Figure 5 shows the corresponding data points on a graph of the predicted deep-learning results.

As shown in Figure 5, in ① the low-mobility region, the pixel importance of the GRAD-RAM images does not focus on the crystal structure, but on the entire image, suggesting that mobility is estimated from the information of the entire image, such as the color of the film. In contrast, the ③ GRAD-RAM images of high mobility focus on periodic structures that indicate crystal structures.

4. Conclusion

In the industrial field of semiconductors, process innovations are crucial to fabricate high-performance semiconductor devices. For example, crystallization of amorphous silicon thin films by ELA enables the development of high-performance smartphones in the display industry.

To improve the acceleration of R&D by CPSs, it is important to develop semiconductor manufacturing systems for novel semiconductor device processes using CPSs such as deep learning. In this paper, we reported on estimating the device characteristics of low-temperature polycrystalline silicon thin-film transistors (LTPS-TFTs) through deep learning.

The quality of the crystallized polysilicon Si was evaluated using optical inspection methods. In addition, we attempted to quantitatively predict the mobility and gate threshold voltage of the LTPS-TFT using deep learning from optical microscope images of the polysilicon film.

RMSPE of the prediction mobilities was 15%, and the RMSPE of prediction V_{th} was 23.3%.

From the results of the GRAD-RAM analysis, in the low-mobility region, the CNN pixel importance of the input images does not focus on the crystal structure, but on the entire image, suggesting that mobility is estimated from the information of the entire image, such as the color of the film. In contrast, the high-mobility GRAD-RAM images focused on the periodic structures of the LTPS films.

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