Experimental Implementation of Reinforcement Learning for Floating Zone Crystal Growth Automation

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Introduction

In Floating Zone (FZ) method crystal growth operation, operators have to adoptively control input parameters by monitoring the status of the crystal and melt in the furnace, and the operation is heavily dependent on human intuition due to complex nonlinear melt dynamics governed by various physics. In our previous study, we proposed automated operation of FZ crystal growth using reinforcement learning (RL) and dynamics prediction via a Gaussian mixture model (GMM) within a simulated environment[1,2]. In this study, we constructed a real, operational FZ furnace prototype to experimentally validate the previously developed data-driven RL control approach.

Experimental Procedures

Automated crystal growth was executed by repeating three sequences: image capture, state parameter extraction via image processing, and RL-based parameter calculation. A camera installed at the furnace window continuously captured images of the crystal and melt states. These images were processed to extract some key parameters like crystal diameter and so on. These parameters were newly selected based on our real FZ furnace operation experience. Then RL operation-model determined optimal input parameters. This RL model was pretrained on human-generated crystal growth data.

Results and Discussion

Newly selected parameters to express the crystal and melt states are three: crystal diameter, melt constriction, and melt outline angle near the crystal. Operators observe crystal diameter to adjust it to ideal value, and others not to drip off or separate melt. These parameters were precisely extracted from crystal and melt images using the outline extraction based on the differential in RGB and HSV color space.

Automated Si crystal growth experiments using the RL model consistently produced silicon crystal. Cross-sectional visual inspection confirmed the monocrystalline nature of the crystals. Figure 1 shows the auto-produced Si crystal and its diameter compared with ideal value. RL model operated FZ furnace to increase crystal diameter. And after the crystal diameter reached 1.9 cm, RL model kept it constant.

These results demonstrate the success of FZ crystal growth automation using our previously developed RL-based method which trained from a small number of human-generated operation data. It implies the method is applicable to other human-dependent material processing techniques.

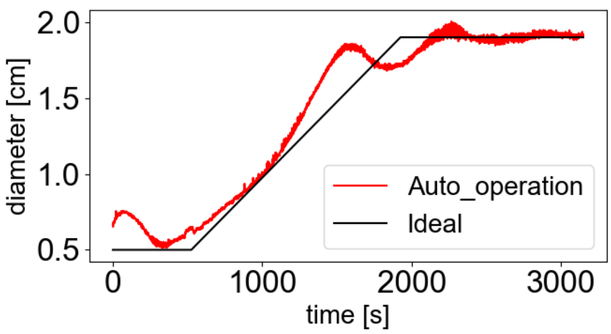

Figure 1 Auto-produced silicon and its diameter compared with ideal value

References

[1] Omae, R., Sumitani, S., Tosa, Y. & Harada, S., Sci. Technol. Adv. Mater.: Methods 2, 294–301 (2022).

[2] Tosa, Y., Omae, R., Matsumoto, R., Sumitani, S. & Harada, S., Sci Rep 13, 7517 (2023).