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Deep Learning Style Transfer for Elastic Image Registration of Visually Distinct Correlative Microscopy Images

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Background

Correlative microscopy involves using multiple imaging techniques on the same sample to enhance the overall understanding of the data by correlating the information gathered from each method. [1] While Correlative Light and Electron Microscopy (CLEM) is an established method in life sciences, its application in materials science remains underutilized yet equally crucial. [2] The primary challenge in materials science correlative microscopy lies in co-localizing and registering (aligning) microstructure images, a task complicated by possible microstructure complexity compared to cellular images. In our previous work, we described a method developed to generate a large dataset of light optical microscope (LOM) and scanning electron microscopy (SEM) images for training a deep learning (DL) model aimed at microstructure image enhancement. [3] To achieve automatic alignment of distinct images, we found it necessary to include Confocal Laser Scanning Microscope (CLSM) images, which serve as a visual intermediary. Despite the Keyence VK-X1100 CLSM being fully automated, software limitations precluded the use of its automation features. This resulted in a bottleneck, as the raw images from mapping could not be saved, forcing reliance on semi-automatic imaging. In addition, too small and unalterable overlap between images hindering further processing. Initially, we trained a deep learning model built on Generative Adversarial Networks (GAN) to enhance LOM images. However, improving this model requires additional data, which is time-consuming to obtain. Therefore, we suggest using the trained model as a style transfer filter to eliminate the need for CLSM images. This approach enables the simulation of SEM appearance from LOM images, thereby assisting the elastic image transformation tool (bUnwarpJ [4]) in identifying common features across images, facilitating their alignment.

Methods

We used pre-aligned images from the aforementioned dataset to effectively demonstrate the success ratio of image registration with the bUnwarpJ ImageJ tool, comparing its performance on both the original and style transferred images. This dataset consists of LOM and SEM-CBS micrographs of TRIP steel (512x512 px, 20x20 µm field of view), which were initially aligned using a workflow detailed in our previous work.[3] We employed 252 image pairs to evaluate our hypothesis. The investigation began with elastic registration on the original LOM (source) and SEM-CBS (target) images, establishing a baseline success rate. Subsequently, a GAN model was introduced to transform LOM images into CBS-like counterparts. This transformation aimed to narrow the visual disparity between LOM and CBS images, facilitating improved registration accuracy by the bUnwarpJ tool. The transformations devised for the predicted images were then applied to the original LOM images to achieve the desired alignment. Given the absence of a robust metric for registration (aligning) quality, evaluations were subjectively categorized into four tiers: poor, bad, decent, good.

Results

Elastic registration from raw LOM to CBS images was notably unsuccessful across the majority of cases (poor: 160, bad: 90, decent: 1, good: 1). This failure is immediately apparent, with the algorithm causing significant distortion and deformation of the source LOM images. In contrast, the application of GAN to transform LOM into CBS-like images resulted in a marked improvement in registration convergence across all examined instances (poor: 0, bad: 0, decent: 8, good: 244), as evidenced by the provided examples. However, the overall quality of this image registration remains a matter of contention. The inherent low quality of LOM images limits the fidelity of their transformation into CBS-like counterparts, leading to inaccuracies particularly in the depiction of grain boundaries. These inaccuracies result in mismatches when aligning to the target CBS image boundaries. Conversely, while CLSM serves as a comparable intermediary and faces similar challenges, it benefits from a precise physics-based acquisition method, which mitigates issues associated with generative model-induced artifacts. However, this approach requires a two-step alignment process: first from LOM to CLSM and then from SEM-CBS to CLSM. This sequential alignment process inherently doubles the potential for error. Furthermore, as previously highlighted, CLSM mapping represents a significant time-consuming bottleneck.

Conclusion

This study demonstrates the value of style transfer in facilitating the alignment of a large volume of corresponding images from different microscopy techniques. Utilizing LOM and SEM microstructure images of TRIP steel (20×20 µm field of view) as a case study, we illustrate the method's potential to bridge the visual modality gap between disparate imaging techniques. Initially, this approach requires the manual creation or clever generation of a dataset of aligned image pairs to train a deep learning model. Once established, this model significantly simplifies the alignment challenges for subsequent and future datasets of a similar nature. Although, utilization of a less complex U-Net model—typically employed for segmentation—could reduce the size of the required training dataset, our work leveraged a more sophisticated GAN model, necessitating a larger dataset. This work underscores the potential for enhancing image registration through preprocessing with GAN-based transformations, effectively addressing modality differences in correlative microscopy.

Graphic:

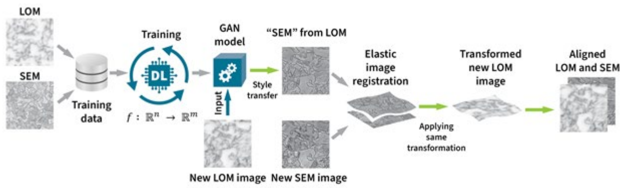

Figure 1: A schematic of image registration utilizing deep learning style transfer.

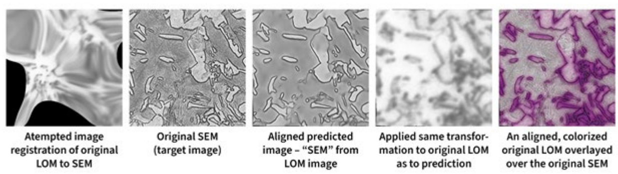

Figure 2: Depiction of image registration failure or success depending on the incorporation of style transfer.

Keywords:

Correlative-microscopy, image-registration, deep-learning, style-transfer

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