Identification of Microparticles from Low Resolution Optical Micrographs by Super Resolution

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Abstract:

Observation of iCVD polymerization *in-situ* is often challenging due to the use of a long-distance focal lens needed to observe the reaction and external motor vibrations from the reactor leading to low resolutions and slight rotation and translation in images captured. In this research, we aim to improve the low resolution retrieved from *in-situ* monitoring and enable identification and characterization of individual polymer particles dispersed and aggregated as clusters. To achieve this, we fine-tune and train the Real-ESRGAN super resolution neural network using pairs of *in-situ* low resolution and *ex-situ* high resolution optical micrographs of 5 µm polystyrene particles dispersed in 5CB liquid crystal (LC), which are used as a surrogate for the polymer particles formed by iCVD. Through pure computer vision techniques, we successfully identify microparticle clusters in the upscaled images and approximate their properties using bounding box approximation. Despite longer training times compared to object detection methods, this method shows promise of identifying and characterizing individual microparticles via binary erosion and promises scalability and generalizability in identifying future microparticle clusters without need for manual identification and loss of spatial awareness of the clusters in the dataset.

Summary of Research:

In order to upscale the low-resolution (LR) *in-situ* images to their high-resolution (HR) *ex-situ* counterparts via super resolution, we focus on isolating the slide containing the microparticle clusters of interest in the images and collect them into a new LR-HR slide pair dataset. This ensures that the clusters are the target of the upscale instead of any extraneous background noise from the image.

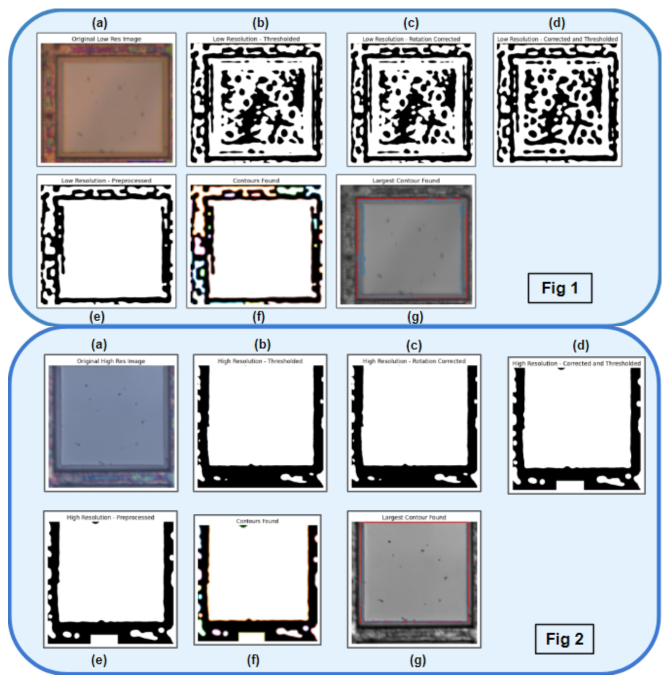
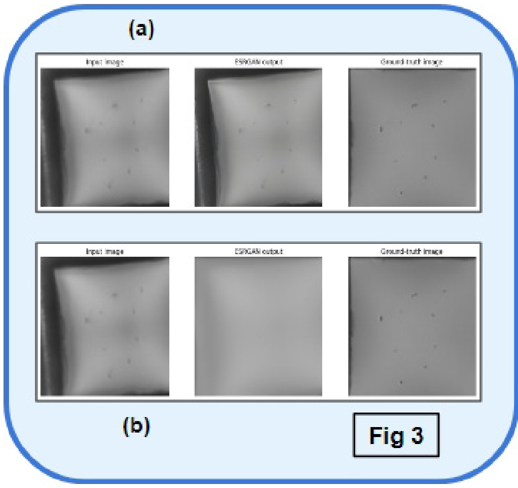


Figure 1, top: Full pipeline identifying the steps needed to isolate and crop the slide from a sample LR image into the new LR-HR slide dataset. Figure 2, bottom: Full pipeline identifying the steps needed to isolate and crop the slide from a HR image into the new LR-HR slide dataset.

Figures 1 and 2 show the computer vision pipeline needed to isolate the slide in the LR/HR images and curate the LR-HR pair dataset to pass to Real-ESRGAN. In order to isolate the slide in the LR images in Figure 1, we start by applying a Gaussian blur ($\sigma = 20$) and an adaptive threshold with a 65 pixel block size to create an initial segmentation of the image into foreground and background [Figure 1a-b].



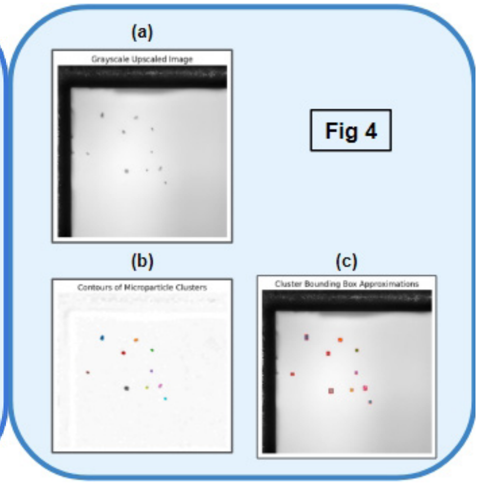


Figure 3, left: Comparison of visual output of super resolution upscaled output between pure inference Real-ESRGAN (a) and fine-tuned Real-ESRGAN (b). Figure 4, right: Process of identifying and characterizing microparticle clusters from the inference upscaled LR images.

To correct for slight rotations, we applied a Hough Transform to both images to rotate them to a top-down POV [Figure 1c]. Another Gaussian blur and adaptive thresholding was run on the rotated images to clean and straighten the thresholds; this was followed by passing the images into an algorithm to fill binary holes in closed shapes and to a binary opening with a square footprint of size 16 to merge various thresholded contours together [Figure 1d-e]. We then use the Marching Squares algorithm on the filled thresholded image, which uses a lookup table to connect lines together in binary images to draw contours and filter the returned contour list by area to identify the largest contour in the image: the slide [Figure 1e-g]. Isolating the slides in the HR images follows the same procedure except for the initial adaptive thresholding, which was changed to Otsu thresholding due to the easier contrast between foreground and background in the provided images [Figure 2]. Both found slides were cropped from their respective image into roughly 800 × 800 image patches to form the LR-HR pair dataset.

Super resolution was done by passing the LR-HR pair dataset into Real-ESRGAN for 4x upscaling. We compare the upscale by running the neural network by pure inference using only the pretrained weights and by fine-tuning the neural network with the weights over the training and validation data for 50 epochs (learning rate = 0.0001). Results were compared between the two groups by visual inspection and by using three image quality metrics: NIQE (Natural Image Quality Evaluator), PSNR (Peak Signal-To-Noise Ratio) and SSIM (Structured Similarity Index Measure). The visual output of the pure inference neural network and fine-tuned neural network for one image are shown in Figures 3a-b.

Over the test set, the average NIQE, PSNR and SSIM for the base network were 10.7, 17.8, 0.90 respectively. For the fine-tuned network, the average NIQE, PSNR and SSIM were 14.0, 22.6 and 0.94 respectively. This indicates that with further training of Real-ESRGAN, the fine-tuned network could perform even better upscaling than inference super resolution alone, though it may take longer to generate than current conventional methods.

In order to identify the microparticle clusters in the upscaled inference images, we applied a morphological reconstruction by erosion and an alternating binary opening and closing followed by the Marching Squares algorithm to identify all contours in the resulting image, which happened to be the clusters themselves [Figures 4a-c].

Properties of the microparticle clusters such as area and circumference were then able to be found via bounding box approximation. Furthermore, the spatial locations of the microparticles and their clusters with respect to each other in the same LC sample are retained in the upscaled images, which will allow for correlating LC local orientations to the particle properties.

Conclusions and Future Steps:

This research shows it is possible to use a super resolution neural network to upscale a LR image and characterize microparticle clusters scalable with the size of the provided dataset and, at the same time, retaining the relative spatial positions of each cluster. With further fine-tuning, it may be possible to characterize clusters in higher definition than can be done with pure super resolution inference. Individual microparticles in the clusters also show promise upon being detected with more investigation. In the future, we plan to fine-tune three data subsets of LR-HR pairs of size 30, 60 and 120 to see if dataset size has an impact on super resolution visual and metric performance and test to see if the super resolution preprocessing and procedure is robust to microparticle clusters of various sizes and types.

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