Supporting Information

Enhanced Nanoparticle Identification Using Momentum-Space Filtering for Interferometric Scattering Microscopy (iSCAT)

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In this Supplementary Information we present and discuss the workflow of our background extraction approach.

Interferometric-scattering based microscopy benefit high sensitivity caused from the interference enhancement. The sensitivity is limited by noise, including uneven illumination and shot noise. Spurious illumination can be removed by median background subtraction or division2. Our approach deals with residual background noise, especially shot-noise in with relatively high frequency components. The workflow is shown in Figure S1a. Isolated distributed noise exists even after median background removal in the spatial domain as shown in Figure S1b, this kind of noise has a relatively high spectral component. To deal with it, our approach introduces frequency components reweighting. Inspired by background extraction in the frequency domain3 and a frequency reweighting algorithm for structured illumination microscopy4, we introduced a low-pass filter and a notch filter to exclude isolated noise and enhance the bright-dark-rings' feather as modeled in previous study [iPSF]. To determine the effective range of the low-pass filter, loss functions of PCC, SSIM and PSNR are introduced to maximize the consistency of processed particle image and the reference model. The optimal range of the low-pass filter can be obtained from the curves shown in Figure S1c. Feather enhanced particles are as shown in Figure S1d, the bright-dark-rings' feather was more obvious than that in Figure S1b. Then, RVT is conducted for curse detection, which is a symmetrical feather-based particle identification method [RVT]. To extract the artifacts after RVT process, a high-pass filter is applied in the spatial domain. The threshold for this filter can be determined by iteration for maximal TP without FP as shown in Figure S1f. Final identified particles are shown in Figure S1g.

The following formulas are widely used for similarity evaluation in imaging processing. The Pearson correlation coefficient, PCC, is calculated using the following equation:

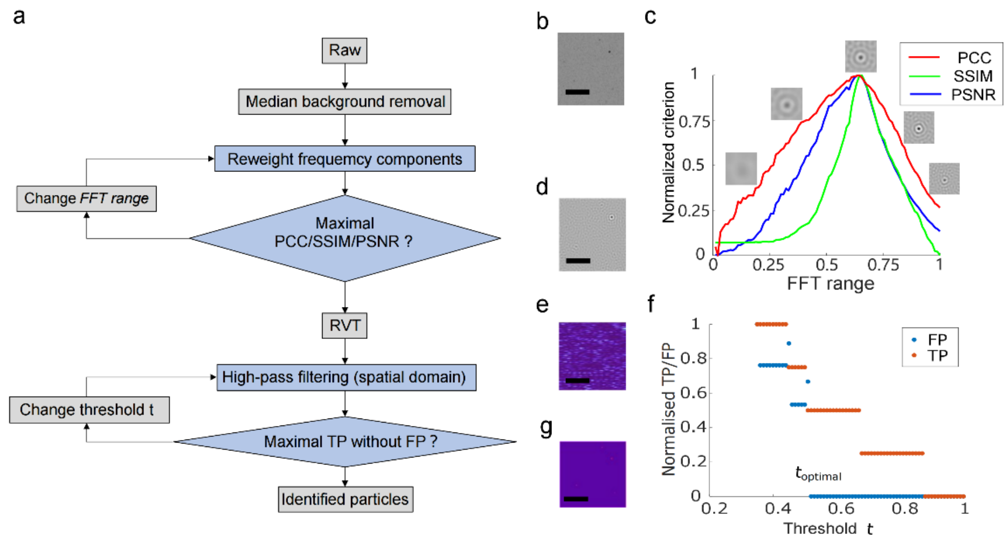

Figure S1: Workflow and intermedia results of the background extraction. (a) Background extraction workflow. (b) Raw image after median background removal. (c) Evaluation of the frequency reweighting under different range in the frequency domain, 3 criterions were introduced here: Pearson correlation coefficient (PCC), Structure similarity index measure (SSIM) and Peak signal-to-noise ratio (PSNR). (d) Deblurred image after frequency components reweighted. (e) Curse particle detection through radial variance transform (RVT)1. (f) Evaluation of the high-pass filter under different threshold t, 3 criterions were introduced here: Ture positive (TP) and False positive (FP). (g) Final image of identified particles.

$$PCC(X,Y) = \frac{\sum_{i=1}^{n}(X_i-\overline{X})(Y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}} \qquad (S2)$$

where n is the number of pixels in each frame of images. X_i and Y_i are the intensity of the i^{th} pixel in images X and Y, respectively, $\overline{X}$ and $\overline{Y}$ correspond to the mean pixel intensity of images X and Y, respectively. The range of PCC is between -1 and 1 with the covariance of pixels in the two images normalized by the product of their standard deviations. When PCC = 1 implies a perfect positive linear relationship between the pixel intensity of the two images.

SSIM adopts 3 perceptual factors as criteria, including luminance, contrast and structural information in the metric data. SSIM is the produce result of these three components. Formally, the SSIM in this study is given by equation (S3):

$$SSIM(X,Y) = l(X,Y) \cdot c(X,Y) \cdot s(X,Y) \qquad (S3)$$

Where 3 factors are given by equation (S4-6) respectively:

$$l(X,Y) = \frac{2\mu_X\mu_Y+c_1}{\mu_X^2+\mu_Y^2+c_1} \qquad (S4)$$

$$c(X,Y) = \frac{2\sigma_X\sigma_Y + c_2}{\sigma_X^2 + \sigma_Y^2 + c_2} \qquad \text{(S5)}$$

$$s(X,Y) = \frac{\sigma_{XY} + c_3}{\sigma_X\sigma_Y + c_3} \qquad \text{(S6)}$$

The PSNR is an evaluation about the peak intensity against the background noise:

$$PSNR = 20 \cdot log_{10}\left(\frac{MAX_I}{\sqrt{MES}}\right) \qquad \text{(S7)}$$

Where the Mean Squared Error (MSE) represents the averaged intensity difference between each pair of pixels in the same position.

$$MSE = \frac{1}{m}\sum_{i=0}^{m-1}\|X(i) - Y(i)\|^2 \qquad \text{(S2)}$$

References

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