

# Automation of Optical Tweezers & Tracking Applications for EV Radii Prediction

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## 1. Radii Prediction & Tracking Methodology

- 1.1 Brownian Diffusion & applied MSD Relationship
- 1.2 Particle Detection & Image Preprocessing
- 1.3 Dynamics Capture Calibration for Single Particle Applications
- 1.4 Accuracy Improvements
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- 2.2 Auto Mode Control Flow
- 2.3 Progress Remarks

# MSD inferred Particle Radius & Diffusivity

# Brownian Diffusion and Mean Squared Displacement (MSD) Relationship

- EV's and other nanoscale particles undergo Brownian motion.
- Nanoscale particle densities stochastically obey the diffusion relation.
- Rearranging yields a linear relationship between particle MSD and lag time.
- With temperature  $T$  and viscosity  $\eta$  the particle radius  $r$  is calculated.

$$\frac{\partial \rho(\vec{x}, t)}{\partial t} = D \nabla^2 \rho(\vec{x}, t), \quad \vec{x} \in \mathbb{R}^d$$

$\Downarrow$

$$\rho(\vec{x}, t) = \frac{1}{(4\pi Dt)^{\frac{n}{2}}} \exp\left(\frac{-|\vec{x}|^2}{4Dt}\right)$$

$\Downarrow$

$$\mathbb{E}[x] = 0, \text{Var}[x] = 2nDt$$

$\Downarrow$

$$\boxed{\frac{\mathbb{E}[x^2]}{2dt} = D = \frac{k_B T}{6\pi\eta r}}$$

# Particle Detection & Image Preprocessing

## 1. Bandpass Filter

- Low-pass truncated 1D Gaussian Convolution:

$$G(x) = \frac{1}{N} \exp\left(\frac{-x^2}{2\sigma^2}\right), \quad x \in [-r \cdot \sigma, +r \cdot \sigma]$$

- High-pass 1D Boxcar Convolution:

$$B(x) = \frac{1}{2r+1}, \quad x \in [-r, r]$$

- Difference of these convolution results:

$$I_{bp}(x, y) = \underbrace{G \star I}_{\text{Low-pass}} - \underbrace{B \star I}_{\text{Long-pass}}$$

## 2. Maximum Detection & Binary Thresholding

- Peak detection via grayscale morphological dilation
- Binary mask (thresholded with hyperparameter)

## 3. Subpixel Refinement

- Particle c.o.m found to subpixel accuracy.

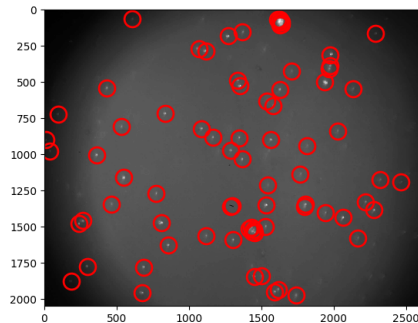
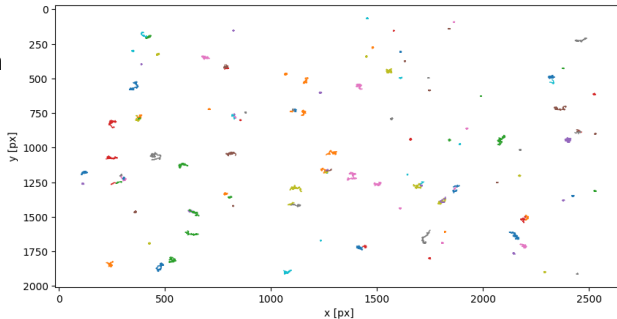


Figure:  $r = 0.5\mu\text{m}$  Polystyrene Detection

# Trajectory Analysis

- Image preprocessing and particle location detection is performed on all frames of captured video.
- **Crocker-Grier** linking algorithm enumerates particles and assigns trajectories.
- Analysis is then free to be performed on returned dataframe.



**Figure:** 2 $\mu$ m Polystyrene Trajectories over 120 frames.

The tracking calibration procedure allows for 5 levels of configuration:

1. Brightness Thresholding & Mask Calibration (frame annotation)
2. Custom Thresholding via Cluster Detection (frame annotation)
3. **Trajectory Linkage & Memory** (dynamics capture)
4. **Ephemeral Trajectory Thresholding** (dynamics capture)
5. Visual Pixel Density / FPS config (physical result calibration)

# Dynamics Capture Calibration

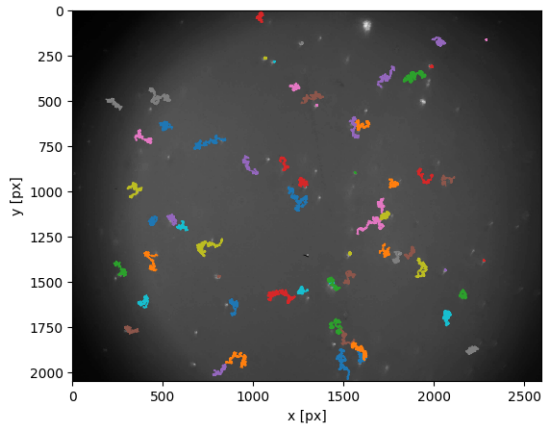


Figure: Short Memory, Long Ephemeral Threshold

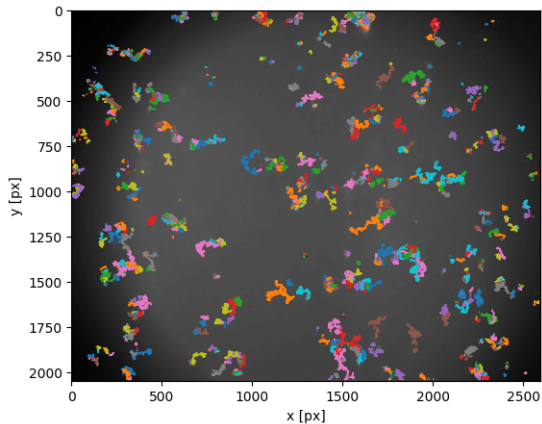


Figure: Long Memory, Short Ephemeral Threshold



# Mean Squared Displacement Plots

- The gradient of the MSD plot permits Diffusivity  $D$  & Radii  $r$  calculation.
- MSD is measured as a function of lag time, returning the average displacement a particle goes through across said lag time, over the entire video sample ( $N$  frames).

$$MSD(\tau) = \frac{1}{N - \tau} \sum_{i=1}^{N-\tau} [(x_{i+\tau} - x_i)^2 + (y_{i+\tau} - y_i)^2]$$

$$\frac{1}{4} \frac{MSD(\tau)}{\tau} = D \quad (\text{For 2D Case})$$

- Larger  $\tau_{max}$ : Richer dynamics captured, high temporal variance.
- Smaller  $\tau_{max}$ : Less complete dynamics, low temporal variance. (more stable)

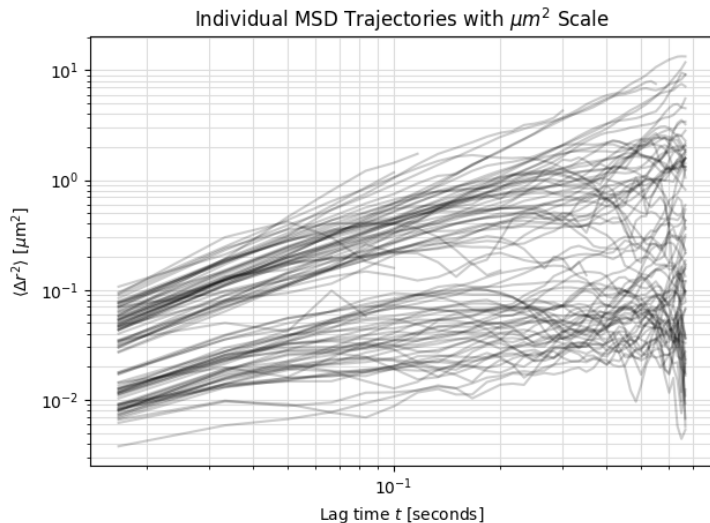


Figure: Individual  $2\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

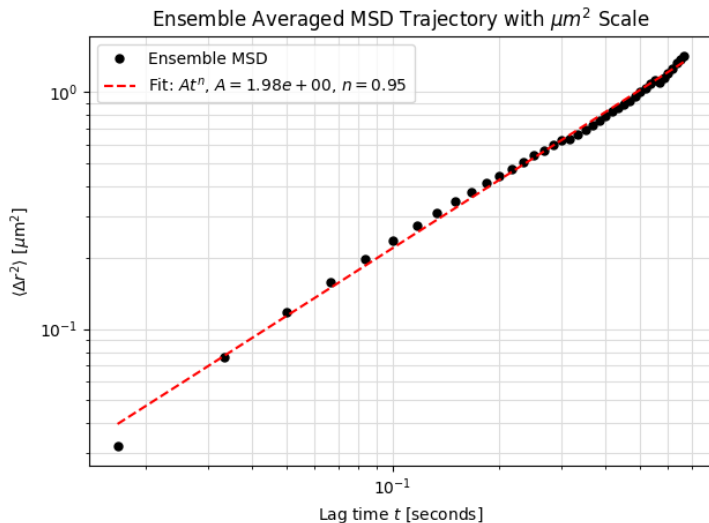


Figure: Ensemble Averaged  $2\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

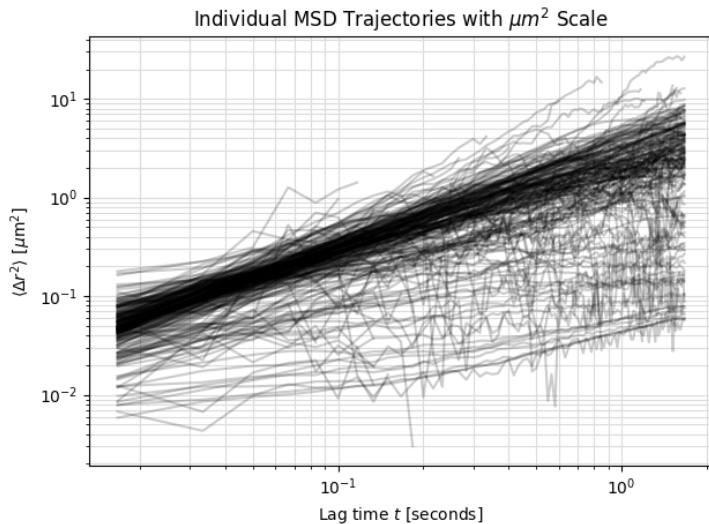


Figure: Individual  $1.04\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

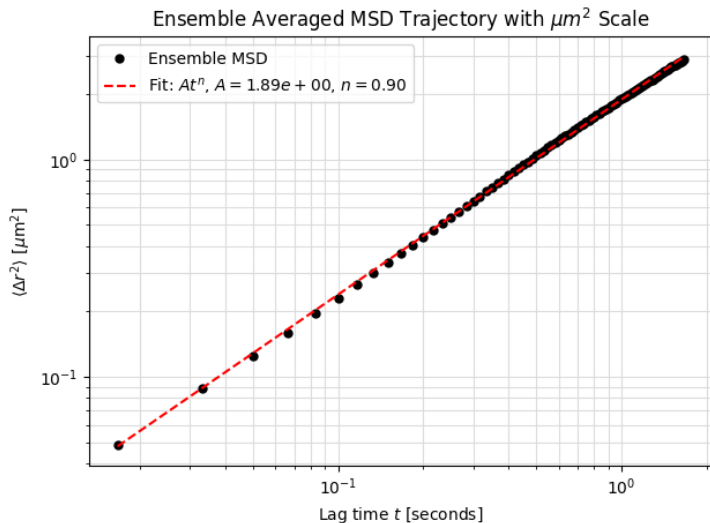


Figure: Ensemble Averaged  $1.04\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

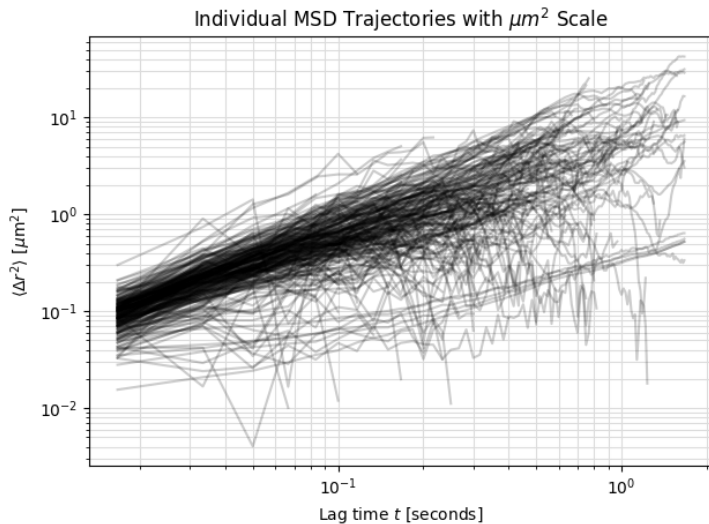


Figure: Individual  $0.53\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

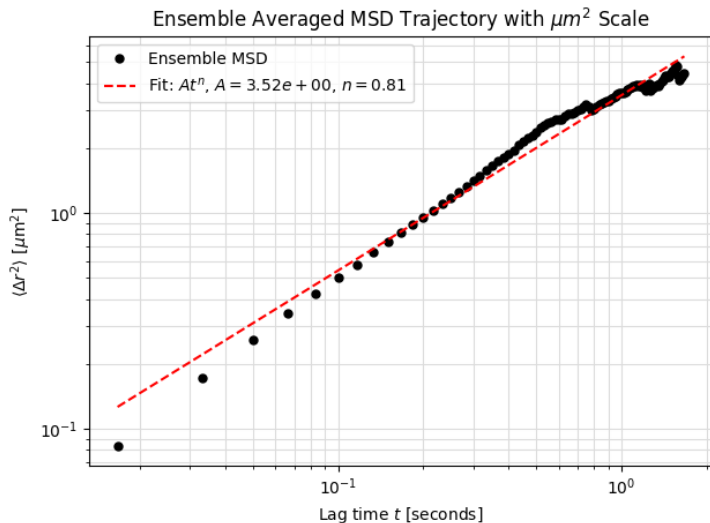


Figure: Ensemble Averaged  $0.53\mu\text{m}$  Polystyrene Mean Squared Displacements fit with 15 frame memory.

# Radii Prediction Accuracy

- The backend takes the gradient of the MSD fit to calculate the radii and diffusivity coefficient:

$$\frac{\mathbb{E}[x^2]}{t} = 4D = \frac{2k_B T}{3\pi\eta r}$$

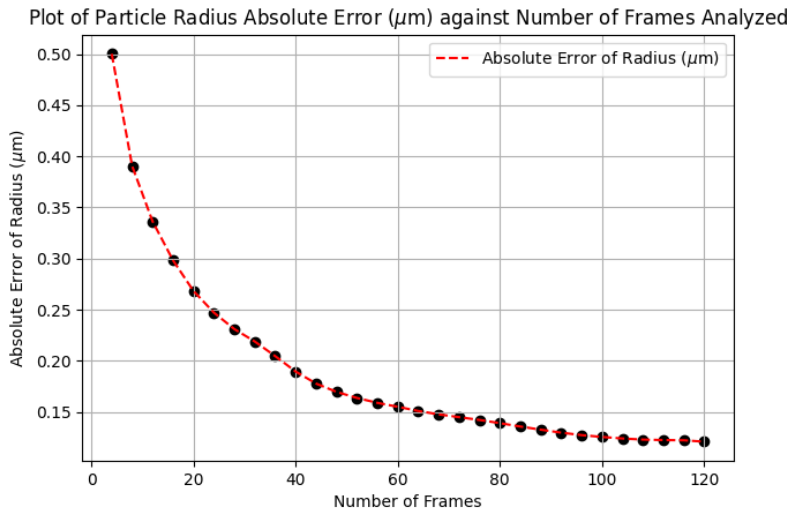
Comparison between Literature Radii Values and Tracking Model Predicted Values for 100 frames			
Real Radii Values ( $\mu m$ )	1	0.52	0.265
Ensemble Predicted Radii Values ( $\mu m$ )	1.022	0.496	0.2303
Absolute Error ( $\mu m$ )	0.022	0.024	0.0347
Relative Error	0.022	0.046	0.1309

Note: These results use long memory, short ephemeral thresholds, and a long  $\tau_{max}$ .

Estimates under this configuration break down for more diffusive particles.



# Radii Prediction Accuracy: Video Length



# Enhancing Stability for Single Particle Measurement

The goal is to strongly fit straight lines to single particle mean squared displacement plots for individual radii calculation.

Solution: **Short Memory, Long Ephemeral Threshold, Small  $\tau_{max}$ .**

- (+) Very small temporal variance, longer trajectories analyzed.
- (-) Hard to ensure that the particle we want has a strong enough track. Only very stable particles are kept (careful calibration of the optical tweezer ROI necessary).

## Before Changes

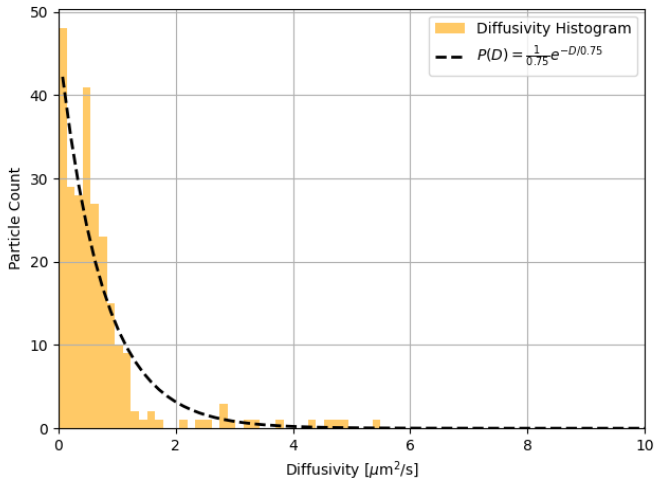


Figure: Diffusivity Histogram 1.04 $\mu\text{m}$  Polystyrene fit with  $\tau_{\text{max}} = 60$

## Before Changes

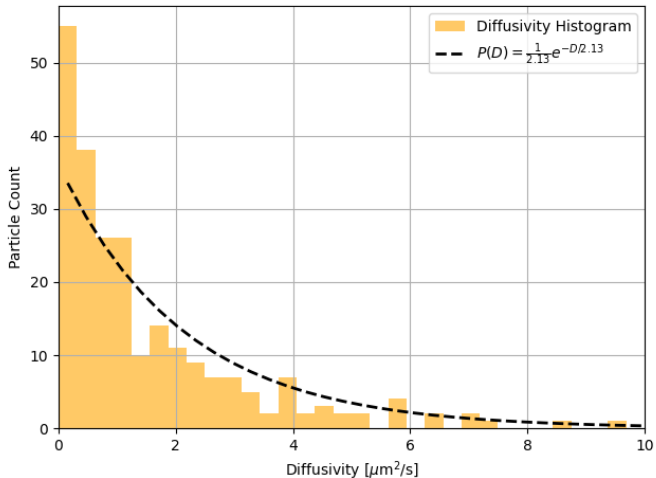


Figure: Diffusivity Histogram 0.53μm Polystyrene fit with  $\tau_{max} = 60$

## Reasoning for observing this exponential distribution (not desired)

- In a very noisy track with high temporal variance, the MSD ceases to be linear and anomalous diffusion begins. The diffusivity  $D_t$  consequently becomes governed by some PDF  $\pi(D, t)$ . (Chubynsky & Slater, 2018)
- One can further say that  $D$  is subject to some arbitrary constant noise  $d_0$  (diffusivity), and bias force  $s_0$  due to this temporal variance in the fit. With  $J = 0$ :

$$J = \frac{-\partial}{\partial D} [d_0 \pi(D, t)] - [s_0 \pi(D, t)]$$

$$\frac{\partial}{\partial D} [d_0 \pi(D, t)] = -[s_0 \pi(D, t)] \implies \boxed{\pi(D) = \frac{1}{D_0} e^{-\frac{D}{D_0}}}$$

- **Smaller particles will have diffusivity distributions of much higher variance! (scales with  $\langle D \rangle^2$ ).**

## After Changes

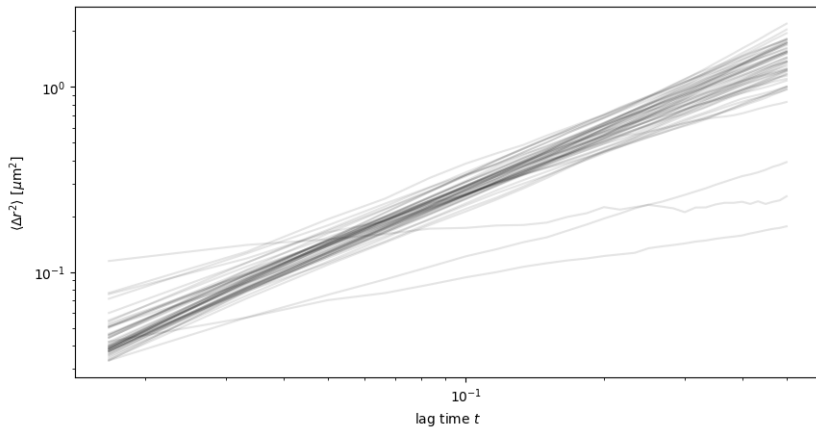


Figure: IMSD PLOT for  $1.04\mu\text{m}$  Polystyrene fit with  $\tau_{max} = 15$

## After Changes

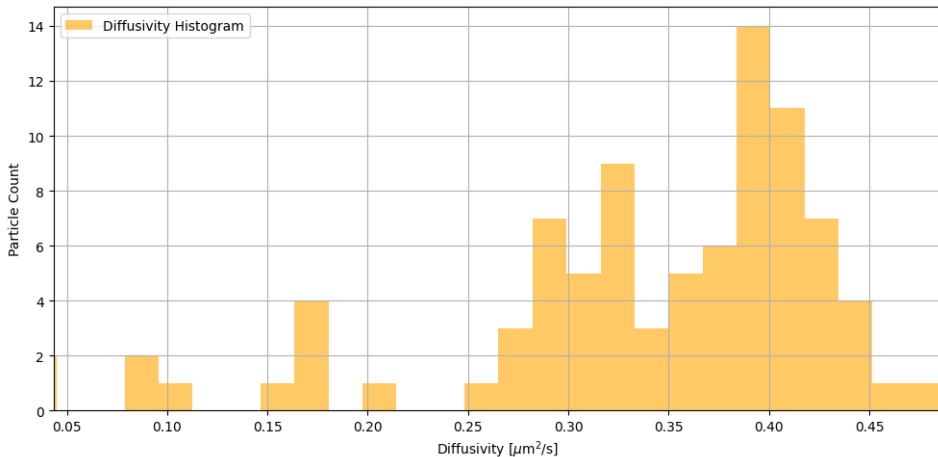


Figure: Diffusivity Histogram 1.04  $\mu\text{m}$  Polystyrene fit with  $\tau_{\text{max}} = 5$

## After Changes

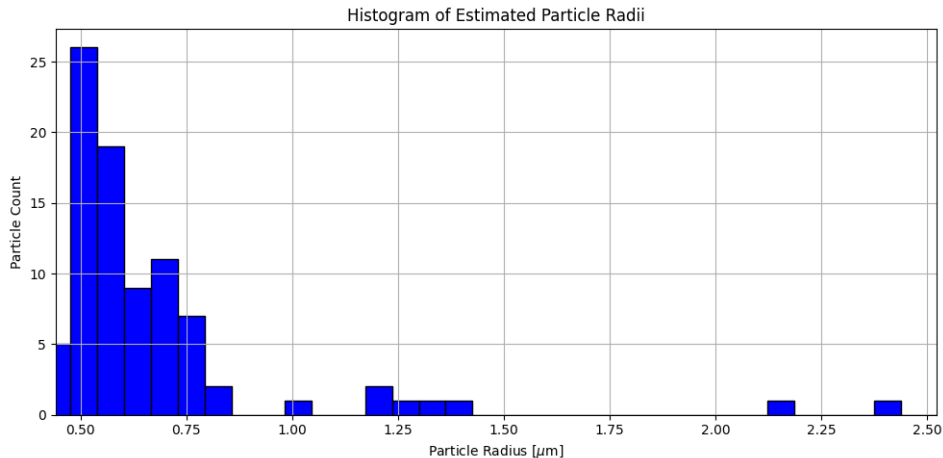


Figure: Radius Histogram 1.04 $\mu\text{m}$  diameter Polystyrene fit with  $\tau_{max} = 5$



## After Changes

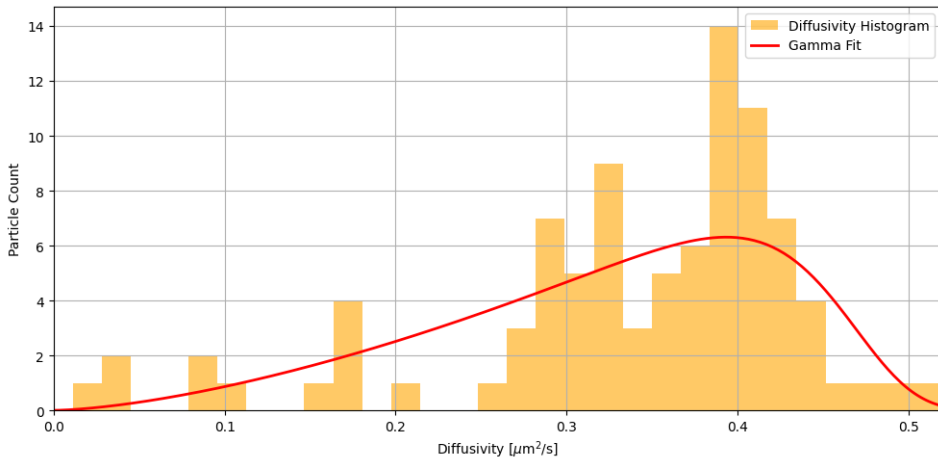


Figure: Diffusivity Histogram 1.04  $\mu\text{m}$  Polystyrene fit with  $\tau_{\text{max}} = 5$

## After Changes

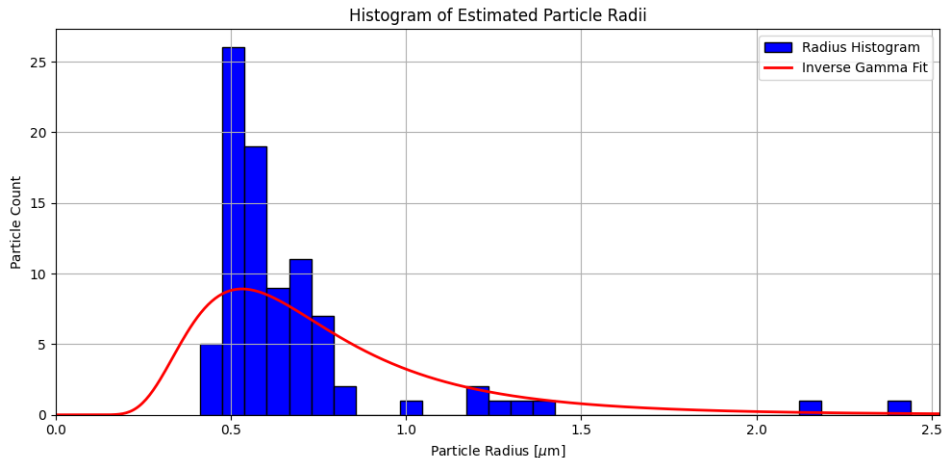


Figure: Radius Histogram 1.04  $\mu\text{m}$  diameter Polystyrene fit with  $\tau_{max} = 5$

# True Distribution of MSD-inferred Diffusivity & Radii

After some calculation, it can be shown that the MSD inferred diffusivity and radius are distributed according to:

$$\pi_D(x; N, D, \tau, d) = \frac{x^{\frac{d(N-\tau)}{2}-1} e^{-\frac{d(N-\tau)x}{2D}}}{\left(\frac{2D}{d(N-\tau)}\right)^{\frac{d(N-\tau)}{2}} \Gamma\left(\frac{d(N-\tau)}{2}\right)} \sim \Gamma\left(\frac{d(N-\tau)}{2}; \frac{2D}{d(N-\tau)}\right)$$

$$\pi_r(x; N, D, d, \tau, T, \eta) = \frac{e^{\left(\frac{-k_B T d(N-\tau)}{12\pi D \eta x}\right)} \left(\frac{k_B T d(N-\tau)}{12\pi D \eta}\right)^{\frac{d(N-\tau)}{2}}}{\Gamma\left(\frac{d(N-\tau)}{2}\right) \cdot x^{\frac{d(N-\tau)}{2}+1}} \sim \text{Inv}\Gamma\left(\frac{d(N-\tau)}{2}; \frac{k_B T d(N-\tau)}{12\pi D \eta}\right)$$

Note: This holds for single points, distributions approximate Gaussians for larger  $\tau_{max}$  by CLT.

# Integration into Visual Interface

- Integrates directly into a visual interface.
- Tracking is performed on a parallel process during operation.
- The tracking pipeline supports individual particle analysis via tagging.
- A jupyter notebook has been made for straightforward tracking calibration to accelerate cross-setup changes.

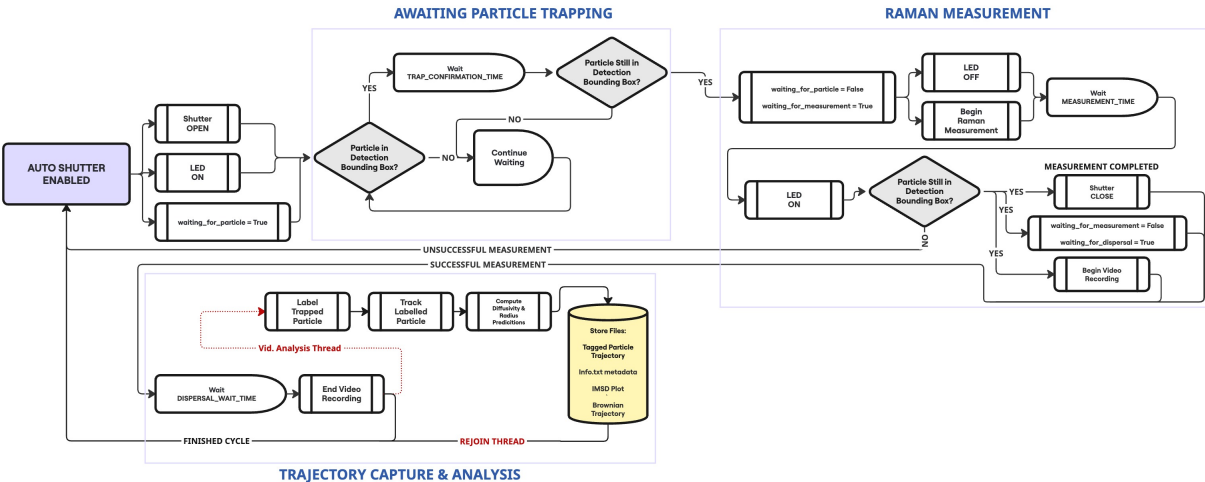
- The following files are returned:
  1. Diffusivity distribution histogram
  2. Radii distribution histogram
  3. Ensemble & Individual mean squared displacement plots
  4. Info text file with values.
  5. Per particle diffusivity/radius csv
  6. Trajectory plots in pixel space
  7. Trajectory csv with enumerated particle trajectories.

# Visual Automation Interface

# About the Visual Interface

- Primary Backends:
  - OpenCV
  - pypylon
  - pythonnet
  - Thorlab's Kinesis SDK
  - Arduino's PyFirmata
  - various other support packages..
- Functionality:
  - Overlaid particle detection
  - Manual detection bounding box adjustment
  - Manual shutter control
  - Screengrabbing & Video
  - Alignment crosshair
  - Radii Estimation (processed concurrently)
  - **Auto Mode** (complete autonomous control)

# Auto Mode Control Flow



# Final Remarks

- All features have been tested simultaneously on a webcam based simulated setup and are working in parallel.
- Programmatic control of isoplane is implemented, but not tested.
- Full testing will be done on the setup once hardware integration is complete.
- The entire visual interface backend is extremely object-based and packaged.
- An extensive documentation detailing custom visual interface creation is on Github with examples.