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Intelligent Optical Tweezers with deep neural network classifiers

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Abstract.
Optical tweezers use light to trap and manipulate mesoscopic scaled particles with high precision making them a useful tool in a plethora of natural sciences, with emphasis on biological applications. In principle, the Brownian-like dynamics reflect trapped particle properties making it a robust source of information. In this work, we exploit this information by plotting histogram based images of $250ms$ of position or displacement used as input to a Convolution Neural Network. Results of 2-fold stratified cross-validation show satisfying classifications between sizes or types of particles: Polystyrene and Polymethilmethacrylate thus highlighting the potential of CNN approaches in faster and non-invasive applications in intelligent opto and microfluidic devices using optical trapping tools.

1 Introduction

Optical Tweezers (OT) makes use of a fine balance between radiation pressure and dipolar forces arising in intense field gradients to manipulate particles at the mesoscopic scale. Furthermore, when integrated with a quadrant-photodetector, see figure 1, OT can also probe the dynamical properties of a trapped particle by tracking the position using the forward scattered light. Recently, it has been shown that these dynamics can be used to identify and classify particles through a careful analysis of the position timeseries and machine learning algorithms, which can be fundamental for future integration into intelligent microfluidic devices[3].

In this work, we present an alternative approach that makes use of deep learning, in particular Convolution Neural Networks (CNN), to classify particles based on information contained in the histogram plots constructed from the position timeseries. More precisely, we explore the capability to differentiate type and size of particles using position based histograms or displacement based histograms.

2 Theoretical framework

Considering that the optical trap is generated by an optical beam of Gaussian intensity profile, the trapping force can be approximated at first order by Hook-type law of harmonic oscillator type. Alone, the trap is the result of a balance between radiation pressure and electromagnetic gradient forces. As the particles are usually immersed in a medium, we should consider also the viscosity, which is fundamental for the trapping process, as well as additional collisions which subject the particle to a confined Brownian-like motion. As a whole, the stochastic dynamics can be described by a Langevin differential equation as

$$m\frac{d^2\mathbf{r}}{dt^2} + \gamma\frac{d\mathbf{r}}{dt} + \boldsymbol{k} \odot \mathbf{r} = \gamma\sqrt{2D}\boldsymbol{\chi}(t), \tag{1}$$

where m is the mass of the particle, γ the friction term between the particle and surrounding medium, D the diffusion coefficient, $\chi(t)$ the stochastic term representing Brownian motion, and k the stiffness coefficient from the Hook law approximation for the Gaussian beam profile.

The physical properties of the Brownian motion reflect both the surrounding medium properties and the trapped particles, making the position timeseries a rich source of information about the system. Also, by subtracting the position at a previous time we obtain the displacement timeseries resulting in another way of investigating the dynamics of the particle. Indeed, despite being dependent on the same physical quantities, position and displacement follow distributions of distinct momentum resulting in two distinct histograms as depicted in figure 1. The trapped particle is in equilibrium with the medium, therefore the position follows the Boltzmann distribution,

$$\rho(x) = \sqrt{\frac{k}{2\pi k_b T}} e^{-\frac{k(x-x_{eq})^2}{2k_b T}}, \tag{2}$$

where k_B is the Boltzmann constant and T the temperature of the system. The displacement follows a zero centered normal distribution with variance given by the mean squared displacement (MSD) which considering the overdamped regime of typical experimental settings results in[1]

$$\mathrm{MSD}(\Delta t) = 2D\tau_{ot}\left(1 - e^{-\Delta t/\tau_{ot}}\right). \tag{3}$$

where Δt is the time interval between consecutive times and $\tau_{ot} = \gamma/k$ is the optical trapping time. If we take

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the time interval between consecutive measurements to be much smaller than the optical trapping characteristic time ($\Delta t << \tau_{ot}$) we have that MSD $\approx 2D\Delta t$, which corresponds to the variance of the displacement for a free particle under Brownian motion.

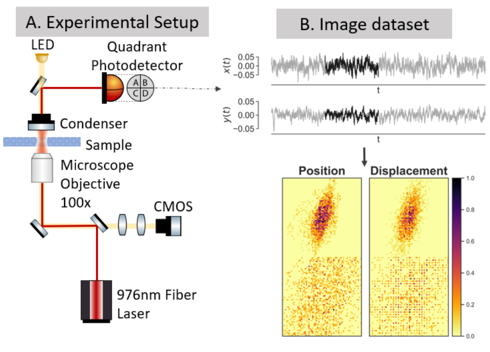

Figure 1. On the left, scheme of OT setup with quadrant photodetector for particle tracking and on the right image plotting procedure.

3 Results

In this work we investigated the capacity of CNN for classification using the forward scattered signal and in particular by looking at the displacement and position histograms retrieved for each particle. With this objective, we used 5 classes of particles: Polystyrene (PS) particles of sizes 3, 4 and $8\mu m$ and Polymethilmethacrylate (PMMA) particles of 3 and $8\mu m$.

For a total of 50 distinct particles (10 for each class) we acquired a signal around $25s$ of duration from the quadrant photodetector, subsequently dividing them into $250ms$ segments which were used to create the images of the histograms that are the training input for the CNN, as illustrated in figure 1. The training and test procedure followed a stratified 2-fold cross-validation.

First, by fixing the size of the particle, we performed a classification based on the material (figure 2). As observed, the displacement based histograms allow better accuracy for the classification (81% average) opposed to the position-based ones (70%).

In a second test, and restricting to same particle type and the $3\mu m$ and $8\mu m$ sizes, we classified the particles based on their size. Here, excellent classification results are obtained for both position and displacement-based histograms, with 86% and 98% average accuracy for PMMA and 99% for PS(see figure 3).

Finally and in conclusion, satisfactory to excellent type and size classification results were obtained, demonstrating the capacity of CNN to classify optically trapped particles of distinct physical properties. Leveraging on the small acquistion time of the technique together with the computational power of CNN, the findings enclosed in this work can motivate future approaches towards faster and of intelligent opto and microfluidic devices involving optical trapping tools.

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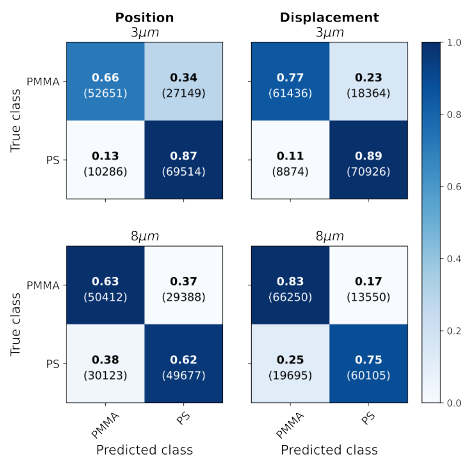

Figure 2. Confusion matrix results of classification between types of particles. Left side results using the position based histograms and right side using displacement based histograms. Top (bottom) row subset of $3\mu m$ ($8\mu m$).

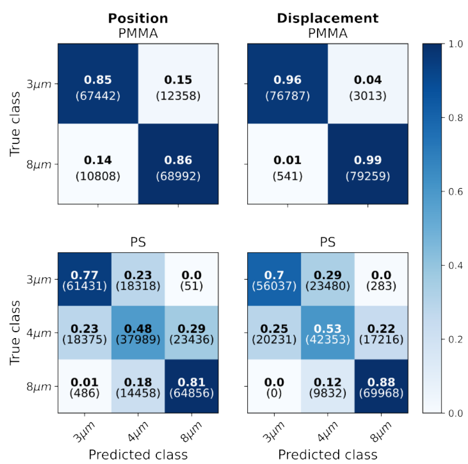

Figure 3. Size classification results between $3\mu m$ and $8\mu m$ of PMMA particles (top row) and $3\mu m$, $4\mu m$ and $8\mu m$ PS particles (bottom row). Left column (right column) is position (displacement) based classification results.