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On the Determination of Diameter and 3D Position of Spray Droplets Using Astigmatic Shadowgraphy and Deep Learning

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Abstract

We present a single-camera approach for estimating the diameter and three-dimensional position of small spray droplets by combining astigmatic shadowgraphy with deep learning. The astigmatism allows an unambiguous depth measurement with a single-camera view and is introduced by placing a cylindrical lens in front of the objective, making the method straightforward to implement on commercially available shadow-sizing systems. The image-processing pipeline combines YOLO for droplet detection and in-plane localization with a VGG16-based convolutional neural network optimized for regression of the depth position and droplet diameter. Both networks were trained exclusively on generalized and augmented synthetic images generated using a Gaussian-based defocus model calibrated to images acquired with the optical setup. The method was evaluated on synthetic images, calibration-target images, and experimental spray images acquired with a micro-scale industrial shadowgraphy system equipped with a cylindrical lens of focal length $f=500$ mm. The network, trained exclusively on

calibrated synthetic images, provided consistent results on experimental data, with estimated uncertainties of 0.15 mm in depth over a 4 mm measurement range and 2.4 μm in diameter for droplets between 20 and 100 μm .

Keywords: Defocus Particle Tracking, Astigmatism, Shadowgraphy, Sprays, Deep-learning, Supervised learning, Synthetic image generator

1 Introduction

The characterization of spray droplets is a fundamental and ubiquitous task in both industrial and academic research, spanning fields from the automotive and aerospace sectors to agricultural, pharmaceutical, and micro-fabrication applications, where drop size and spatial distribution directly control processes such as combustion, coating, cooling, and deposition [1]. Owing to this broad relevance, a wide variety of measurement techniques have been developed over the years for the sizing and localization of droplets and particles in flows, and they continue to be developed to provide more flexible and accurate tools, as documented in comprehensive reviews of optical particle characterization and spray diagnostics [2, 3].

Established optical techniques for drop sizing include point-wise and planar methods with different working principles and ranges of applicability. Phase Doppler techniques provide accurate, time-resolved measurements of drop size and velocity at a single point, but require optically homogeneous spherical drops and a traversing procedure to map an entire spray [4]. Interferometric laser imaging for droplet sizing (ILIDS/IPI) extends the measurement to a plane by analyzing the fringe patterns of out-of-focus glare points [5], while digital in-line holography reconstructs the three-dimensional (3D) position and size of drops from the recorded diffraction patterns, at the cost of a computationally intensive reconstruction and a limited depth accuracy along the optical axis [6]. These techniques are powerful, but they typically rely on coherent illumination, dilute conditions, or complex optical arrangements that are not always compatible with industrial environments.

Another widespread approach for spray characterization is shadowgraphy, or direct backlight imaging. It uses a simple optical setup—a single camera and an incoherent light source—and works with non-spherical and opaque droplets. This technique provides direct visualization of a volumetric subset of the spray structure. Image-processing methodologies have been developed to measure drop size and morphology from shadow images, including rigorous treatments of the effect of defocus on the apparent drop contour and on the effective measurement volume [7]. Conventional shadowgraphy is a mature technique and already available in dedicated commercial systems, such as the ShadowSizer from Dantec Dynamics used in this work [8]. However, it is inherently two-dimensional: The out-of-plane coordinate of the drops is unknown, and defocused drops must either be corrected or rejected. A natural evolution is therefore to exploit, rather than discard, the defocus information encoded in the images. 3D particle localization using defocusing, also referred to as defocus particle tracking (DPT), is a well-established technique in the particle tracking velocimetry

community. Following the seminal work of Willert and Gharib [9], DPT has been used extensively in microfluidic applications [10–14] and also in different domains such as multiphase and turbulent flows [15–17].

Much less explored is defocusing applied to shadographic images. Zhou et al. [18] have recently proposed a method, referred to as depth from defocus (DFD), that combines shadowgraphy and defocusing to determine the 3D position and size of spray droplets. The DFD technique has been extended to calibration-free approaches [19] and higher resolution [20]. However, in this configuration, two cameras are typically required to resolve the ambiguity originating from the symmetry of the defocus function relative to the focal plane. One way to eliminate this ambiguity is to introduce a controlled astigmatic aberration through a cylindrical lens. The resulting defocused images have elliptical shapes with different orientations depending on whether the particle lies in the lower or upper part of the measurement volume. This concept, referred to as astigmatism particle tracking velocimetry (APTV), is a well-known DPT approach used for 3D particle tracking based on fluorescent monodisperse particles for which dedicated calibration procedures [21, 22] and design optimization criteria [23–25] have been established. However, for the case of astigmatic shadographic images of polydisperse particles, there is no established theoretical model for the generation of reliable synthetic images. Furthermore, the calibration becomes very challenging for a single-camera astigmatic system due to the increased degrees of freedom and the greater variability of the images.

The recent advances in deep learning (DL) have made this type of inverse problem more tractable by enabling complex mappings between defocused image features, droplet diameter, and depth position to be learned from suitable training data. In the specific context of defocus- and astigmatism-based measurements, cascaded CNNs have been used to determine the 3D position of particles [26, 27], and dedicated architectures have been proposed for the localization of particles in astigmatic optical setups with overlapping particle images [28, 29]. Systematic comparisons have shown that neural-network-based evaluations of conventional defocused particle images can outperform classical methods based on model functions or cross-correlation, particularly at high particle concentrations [30, 31]. DL approaches have also shown great potential in related complex tasks, including simultaneous detection and sizing of fluorescent particles [32] and measuring the 3D position and orientation of defocused non-spherical objects, such as microscopic swimmers [33].

In the present work, we apply astigmatic shadographic imaging to simultaneously determine the size and 3D position of polydisperse spray droplets observed with a single-camera system. This is achieved with a CNN model trained on experimentally calibrated synthetic images. A typical micro-scale industrial shadow sizing system is equipped with a cylindrical lens to introduce a controlled astigmatism, and the resulting images are processed with a two-stage CNN pipeline: the YOLO object detection algorithm [34] is used to detect and crop the individual droplet images, including overlapping ones, while a regression network based on the VGG16 architecture [35] predicts the depth position z and diameter d of each droplet. The method is validated

against synthetic images generated using ray-tracing simulations [36], and is subsequently applied, without any retraining, to experimental images of a calibration target and of water droplets in a spray.

2 Material and methods

2.1 Synthetic images generation

Training a supervised model requires a large dataset of droplet images with known ground-truth depth position z and diameter d . Such a dataset cannot easily be

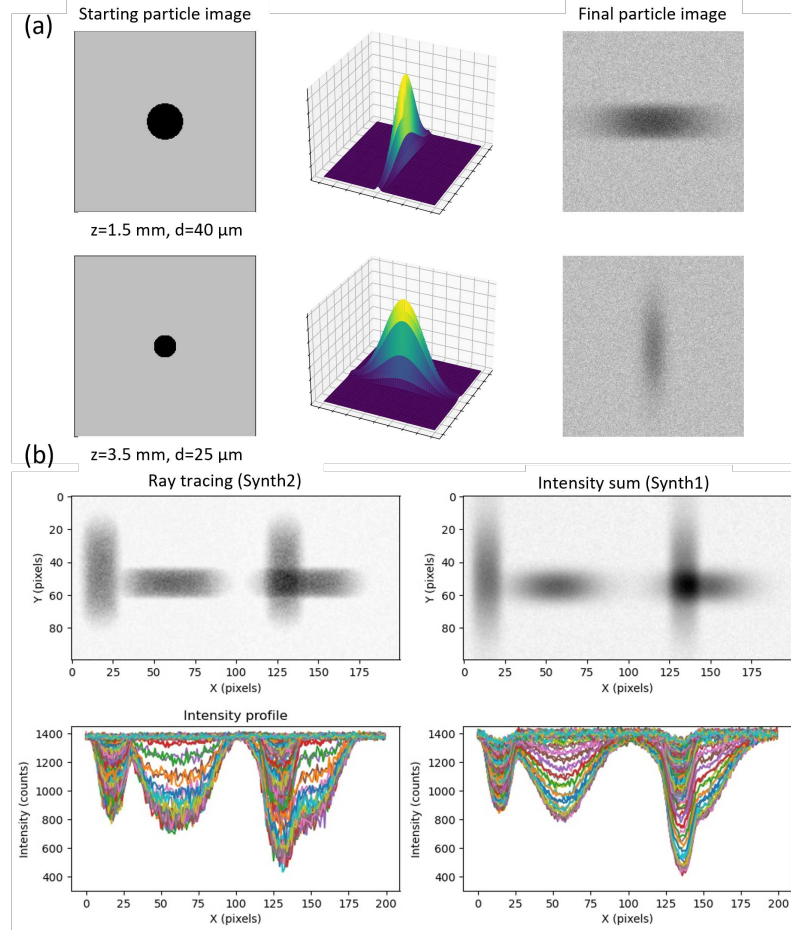


Fig. 1 a) Generation of Synth1 images: starting binary particle image (left), astigmatic intensity distribution computed from the model of Rossi and Kähler [24] (center), and final synthetic image with calibrated background and noise (right), shown for two droplets at different depth positions and diameters. b) Overlapping droplets generated with ray tracing (Synth2, left) and with intensity summation (Synth1, right), with the corresponding intensity profiles, showing that the choice of overlap treatment (ray tracing vs. intensity summation) has a negligible effect on the resulting images.

obtained from experiments: spray droplets are polydisperse, and no practical procedure allows for collecting droplets of known size while independently varying their depth position over the whole measurement range. The training must therefore rely on artificially constructed images, and the central question becomes how reliably a model trained on synthetic data transfers to real experimental images.

In this work, we use two different approaches for synthetic image generation. The first one, referred to as Synth1, is based on the Gaussian approximation of the point spread function (PSF) and is the model commonly adopted in DFD studies [18, 37]. To account for the astigmatic aberrations, we used a modified PSF based on a two-dimensional Gaussian function following the theory developed in Rossi and Kähler [24]

$$\text{PSF}(X, Y, z) = \frac{1}{\pi a_x(z) a_y(z)} \exp \left[-2 \left(\frac{X^2}{a_x(z)^2} + \frac{Y^2}{a_y(z)^2} \right) \right] \quad (1)$$

where a_x and a_y depend on the depth position z . We use here capital letters (X, Y) for coordinates in the image plane with values in pixels, and lowercase letters (x, y, z) for coordinates in the object space with values in mm.

$$a_x(z) = \sqrt{c_1^2 (z - \Delta z_{fp})^2 + c_2^2} \quad (2)$$

$$a_y(z) = \sqrt{c_1^2 (z + \Delta z_{fp})^2 + c_2^2} \quad (3)$$

and c_1 , c_2 , and Δz_{fp} are empirical parameters fitted from experimental images. In particular, for the case at hand, experimental images of the calibration target, described in Sec. 2.3 have been used. The generation process is illustrated in Fig. 1a: starting from a binary particle image of given diameter d

$$B(X, Y, d) = \begin{cases} 1, & \text{if } X^2 + Y^2 \leq (Md/l_{\text{px}})^2, \\ 0, & \text{otherwise,} \end{cases} \quad (4)$$

with M the magnification of the optical system and l_{px} the pixel length, an astigmatic image of a particle at coordinates $\{X_i, Y_i, z_i\}$ with diameter d_i is obtained by a convolution with the corresponding PSF

$$A_i(X, Y) = B(X - X_i, Y - Y_i, d_i) * \text{PSF}(X, Y, z_i). \quad (5)$$

The final brightfield image is obtained by summing up all the astigmatic particle images, scaling and inverting the intensity and adding Gaussian random noise

$$I(X, Y) = I_0 - \alpha \sum_i A_i(X, Y) + \sigma_{\text{noise}}(X, Y), \quad (6)$$

where I_0 and α are constants and $\sigma_{\text{noise}}(X, Y)$ is Gaussian random noise. The values of these parameters are again obtained from comparison with reference experimental images. Being analytical, this model is computationally inexpensive and suitable for generating large training datasets.

The second approach, referred to as Synth2, uses the ray-tracing-based synthetic image generator MicroSIG [36], adapted here to brightfield illumination [31], with the droplets treated as opaque objects blocking the rays from the light source. This model is computationally more expensive but physically more accurate, since it can account for simple image aberration and a more realistic treatment of overlapping particles. In this work, Synth1 was used for training and validation of the networks, whereas Synth2 was used exclusively as an independent test set. Since the two datasets rely on different image formation models, the performance on Synth2 provides a first controlled assessment of the generalization capability of the model before its application to experimental images.

A final aspect concerns overlapping droplet images, which occur frequently in sprays. In Synth1, overlaps are handled by simply summing the intensities, whereas in Synth2 the rays blocked by one droplet are cut out, so that occlusion is treated in a more realistic way. The comparison in Fig. 1b, which shows the same overlapping configuration generated using the two approaches together with the corresponding intensity profiles, indicates that the differences between the two methods are negligible, both qualitatively and quantitatively. This justifies the use of the simpler intensity summation for the training data, which includes both single and overlapping droplets.

2.2 Deep learning tool

The current problem includes the two sub-tasks of (i) droplet detection and localization and (ii) droplet depth position and diameter prediction (regression). In the proposed approach, both tasks are addressed using Convolutional Neural Networks (CNN). The CNN are trained on a large labelled dataset of astigmatic droplets of different sizes and positions, generated with the procedure described in the previous sections.

The final implemented CNN architecture is presented in Fig. 2 and consists of two subsequent CNN networks for the localization and regression tasks, respectively. YOLO (You Only Look Once) [34], an object detection algorithm, is implemented to detect spray droplets and determine their in-plane position. In this case, we used YOLO v-12, which has already been optimized for tasks including overlapping objects (Fig. 2a). A pretrained YOLO12s (small) is trained with 800 grayscale synthetic 1024×1024 images with 30 - 60 randomly distributed particles per image. The model was trained for 30 epochs with a batch size of 16 and validated with 200 images.

For the regression task, used to determine the depth position z and diameter d , we used the VGG16 (Visual Geometry Group) [35] architecture that showed the best prediction after testing various architectures. This architecture was initially designed for classification tasks, and to handle regression tasks, we added a Flattened layer and two Dense layers with ReLU activators, each followed by Dropout layers and a Dense output layer with a Linear activator (Fig. 2b). A similar architecture was already successfully applied to predict orientation and depth position of microscopic defocused objects [33]. A pretrained model for our modified VGG16 with an input size consisting of a single channel with 250×250 pixels was not directly available, and the model was trained without any initial weights. Training and validation loss showed good convergence without any overfitting after 38 epochs, as reported in Fig 2c.

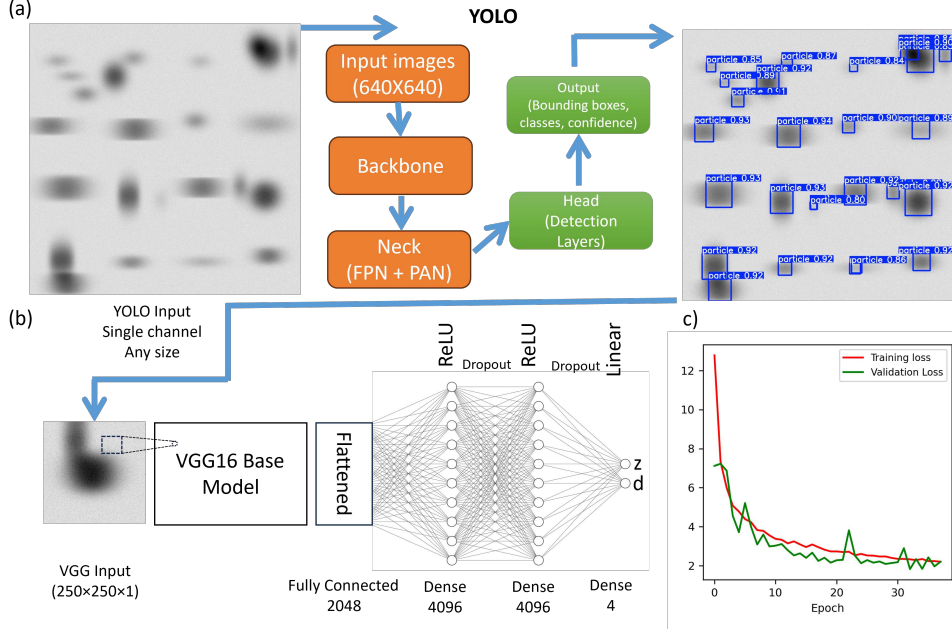


Fig. 2 a) YOLO v12 implemented for droplet detection. Detection results of pretrained YOLOv12s trained on 800 1024 $\times$ 1024 synthetic images of droplets with different diameters (d), XY, and depth positions (z). b) modified VGG16 with a Flattened layer and two Dense layers with ReLU activators, each followed by Dropout layers and a Dense output layer with a Linear activator, and with a 250 $\times$ 250 input shape for the regression task to predict z and d , c) VGG16 training and validation loss on 5000 synthetic images. Each image includes one main particle whose predicted z and d values belong to it, and is located in the center of the image, and up to two randomly distributed particles to simulate an overlapping scenario.

2.3 Experimental setup

The measurement setup consisted of a micro-scale industrial shadow sizing system (ShadowSizer, Dantec Dynamics, Skovlunde, Denmark) that was modified by the addition of a cylindrical lens ($f=500$ mm) along the optical path. Interestingly, the best results were obtained by placing the cylindrical lens in front of the lens (see Fig. 3a), whereas in common astigmatic systems, the cylindrical lens is always placed directly in front of the camera sensor, before the lens objective [24]. The cylindrical lens was inserted with a custom 3D-printed holder that could be inserted directly in front of the long-range microscope objective, and easily adjusted and blocked at the right distance. The back illumination was provided by a 25-mm-aperture, 469 nm pulsed LED unit with an adjustable beam. The 5.5-megapixel-resolution camera (HiSense Zyla, Dantec Dynamics, Skovlunde, Denmark) was equipped with a 6 $\times$ fixed-magnification objective with 70 mm working distance, providing a Field of View (FoV) of 2.7 $\times$ 2.3 mm². The objective lens in combination with the cylindrical lens, provided a usable defocus distance (measurement depth) of 4 mm.

The experimental images were collected on two different setups. In the first setup, shadow size calibration images were acquired on a glass target with a multi-frequency

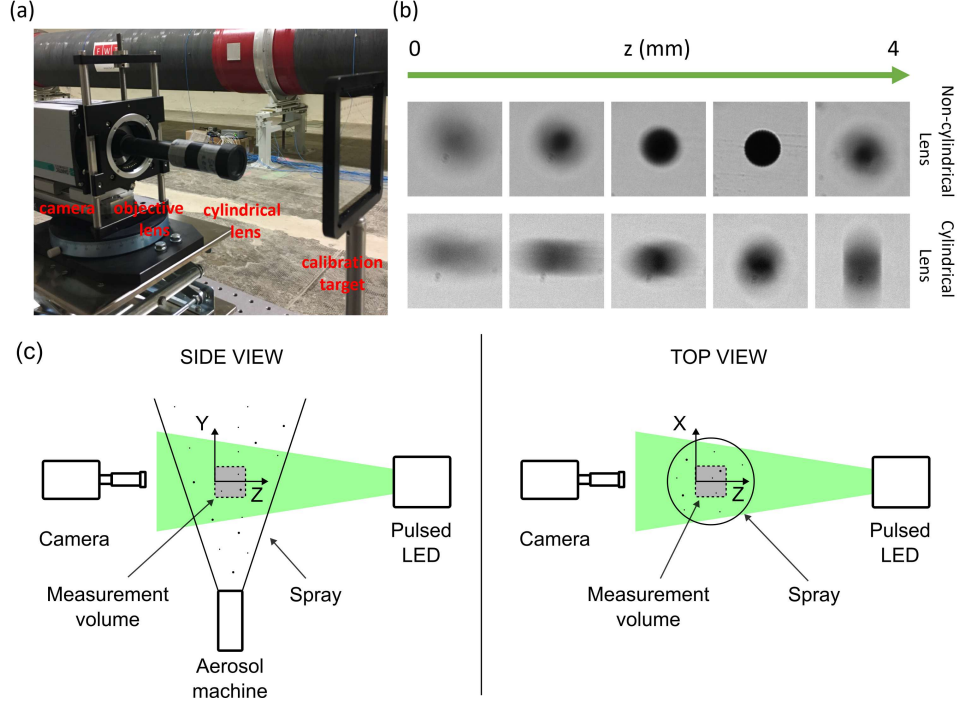


Fig. 3 a) Schematic of the setup with a calibration target, a cylindrical lens is placed in front of the objective lens for astigmatic imaging. b) Experimental images of the droplet in different z positions with and without the cylindrical lens. c) Diagram of the experimental setup for the aerosol measurements (left: side view, right: top view). The measurement volume, shown in gray, is entirely within the aerosol spray volume.

grid distortion pattern, composed of circular dots of varying sizes (ShadowSizer, Dantec Dynamics, Skovlunde, Denmark). The target was displaced in the depth position using a high-precision motorized stage with a resolution of $0.8 \mu\text{m}$ (Thorlabs, Sweden). For the optical arrangements used in this work, we used five dot diameters (21, 40, 48, 76, and $97 \mu\text{m}$), and we displaced the target across the measurement depth of 4 mm with increments of 0.1 mm . The calibration target is shown in Fig. 3a, and typical calibration images can be seen in Fig. 3b. It can be noticed that without the cylindrical lens, there is an ambiguity in identifying the dots before or after the focus position. With the astigmatic aberration introduced by the cylindrical lens, it is possible to determine the z -position of the particle from its defocus shape without ambiguity.

In the second setup shown in Fig. 3c, the same optical setup was used to acquire experimental images of water droplets produced by a commercial Mefar aerosol generator designed primarily for inhalation therapy. The machine generates an aerosol with a Mass Median Aerodynamic Diameter (MMAD) of $25 \mu\text{m}$ through a nozzle with a diameter of approximately 0.6 mm . The measurement volume was located in the central part of the jet where a uniform distribution of droplets was expected. The dimensions of the measurement were the same as the previous experiment, namely $2.7 \times 2.3 \times 4 \text{ mm}^3$.

3 Results and discussion

The core idea of this work is to train CNN models using calibrated synthetic images and subsequently apply the trained model directly to the characterization of experimental sprays. A direct validation and assessment of this approach is inherently challenging, since the ground truth for experimental images is clearly not available. Moreover, designing a reference experiment is not straightforward, as no existing experimental technique can simultaneously provide 3D droplet localization and sizing for sub-millimetric spray droplets with comparable accuracy. For these reasons, we evaluate the proposed methodology through three complementary validation tests: (i) a comparison using synthetic images generated by an independent image-generation approach, (ii) an analysis of experimental images acquired from a calibration target with known ground truth, and (iii) an application to a real spray, where the model performance is assessed through the statistical properties of the measured droplet population.

3.1 Synthetic images

We start with testing the model on the second group of synthetic data (Synth2), created with a different approach (see Sec. 2.1), but calibrated on the same optical setup as the training images (Synth1). We start comparing the results of the regression task (z and d), starting from cropped individual particle images. The value $z = 0$ mm is arbitrarily assigned to the boundary of the measurement depth closest to the objective lens.

Fig. 4 a and b show the predicted results and true values for depth position and diameter of Synth2 images. The results show, in general, a reliable prediction with median errors of 0.174 mm (in the range of 4 mm) and 2.172 μm (in the range of 20-100 μm) for z and d , respectively. A significant deviation is observed only in the depth determination and consistently for all particle diameters, for z positions smaller than 1 mm, as shown in Fig. 4a. The origin of these discrepancies is evident by plotting sample images from the two different synthetic data sets (Fig. 4c), and most likely is due to the effect of spherical aberration, included in Synth2 images. Interestingly, no comparable discrepancy is observed in the diameter estimation, suggesting that diameter estimation is intrinsically more robust to inaccuracies in the modeling of the optical system.

The next step is to assess the impact of overlapping particles on the final results. For this purpose, the complete measurement pipeline was employed. First, the YOLO network detects the particles and estimates their X and Y coordinates. The detected particle images are then cropped and passed to the VGG network, which predicts the corresponding depth position z and diameter d . To assess the uncertainty, we designed a structured testing dataset in which each image has 16 target particles with known 3D positions and diameters, and some randomly distributed particle images are added to simulate different overlapping scenarios. Results were evaluated on 100 test images generated with Synth1, corresponding to a total of 1600 target droplet images. YOLO was able to detect droplet images with a mean Average Precision calculated at a fixed intersection-over-union (IoU) threshold of 0.5 of 98% (Fig. 5a and b). By combining

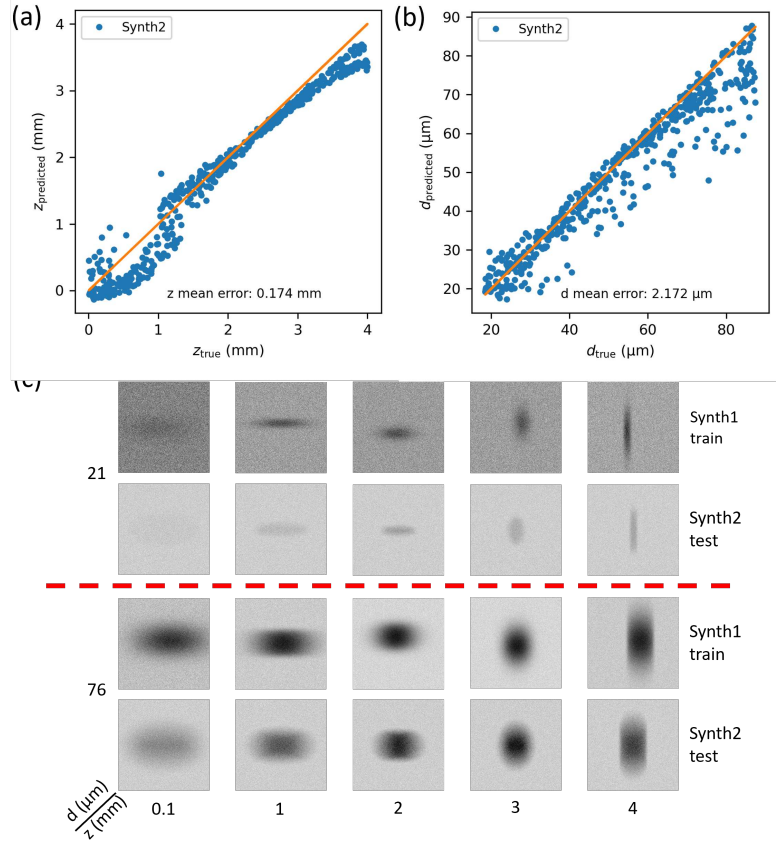


Fig. 4 a) and b) show the z and d prediction results of the model trained with Synth1 data and tested on Synth2 images. c) shows Synth1 and Synth2 images in different z positions and two different diameters of 21 and 76 μm. Synth1 was used for training and validating both VGG16 and YOLO, and Synth2 was used for testing.

YOLO and VGG, we are able to automatically detect spray droplets and define z and d for each of them. In this test case, the method was able to predict the z and d for the 1600 target droplets with a mean absolute error of 0.095 mm and 2.16 μm, respectively (Fig. 5c and d). As a reference, when the exact location of each particle is known (no YOLO), and only VGG is applied to the cropped 250×250 pixel images — with at most two overlapping particles per frame — the mean absolute error was 0.075 mm for z and 1.44 μm for d . This isolates the VGG prediction error from the additional error introduced by YOLO detection.

3.2 Calibration target

The trained network was used to predict the depth z and diameter d of experimental images taken on the calibration target, and compared with reference Synth1 images. It should also be noted that no experimental images were included in the training

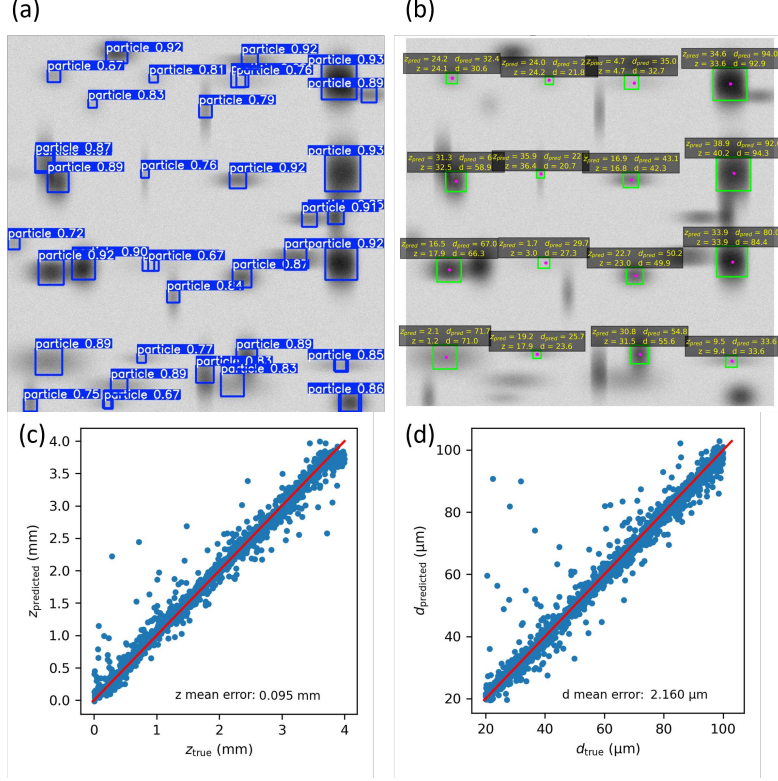


Fig. 5 a) 1024×1024 synthetic images includes 16 main structurally distributed particles and some randomly distributed droplets for simulating overlapping and all droplets detected by YOLO, b) main 16 particles detected by YOLO and depth position and diameter of each droplet predicted (by VGG) vs true values, c) and d) z and d predicted vs true values of the droplets located by YOLO.

of the VGG16. The localization step was not used here since the dots were already positioned on a regular grid and no overlapping particles were present. A set of both group images is presented in Fig. 6 a-b to illustrate the similarities and differences. In order to generalize the model to be able to deal with experimental images, different data augmentation techniques were applied in the training setup, such as artificial noise and lighting. Moreover, centering the particles in the frame in experimental images could be a challenge due to astigmatism and different shapes, so the model was also trained to be able to keep functionality for particle images with small random position offsets from the central position. The predicted versus true data are presented in Fig. 6 c-d, indicating, in general, a remarkably accurate prediction for the experimental images in the z and d determination, with a median error of 0.149 mm (4 mm range) and 2.41 μ m (20-100 μ m range), respectively. The model fails to give accurate results only for the small dots of 20- μ m diameter, where a significant bias error is observed in the bottom and top part of the measurement depth.

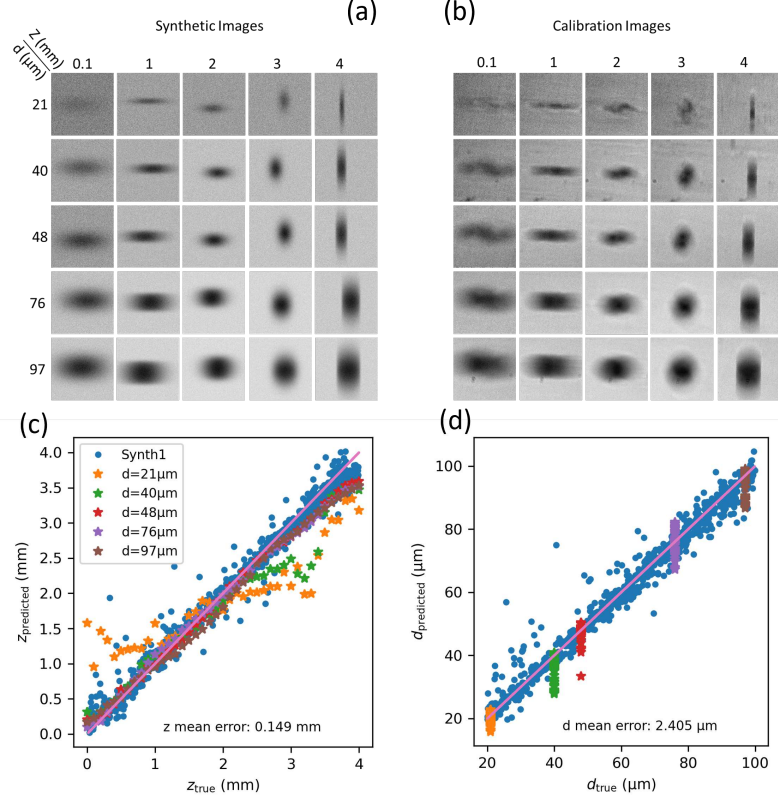


Fig. 6 a) and b) Samples of the Synth1 dataset which were used for training vs experimental images of calibration target which were implemented for testing the model, b) Prediction vs true values of z for droplets with different diameters, c) Prediction of d of images of calibration target and Synth1 data set.

3.3 Sprayed droplets

Finally, we tested the trained model on images of sprayed water droplets. Fig. 7a shows an exemplary recorded image of the spray of droplets taken with the astigmatic setup. After processing with the combined YOLO and modified VGG16 networks, all detected droplets are assigned their corresponding 3D coordinates and diameters (x , y , z , and d). Fig. 7b shows the results of some of the droplets, and as can be seen from the images, the model was able to deal with single (images with red border) and overlapped (images with yellow border) droplets. A key difficulty with the sprayed droplets was that the high droplet density in some images made it hard to isolate a single particle within a 250×250 frame, and it also caused particles to overlap. Because the modified VGG16 was trained on synthetic images of overlapping droplets, the model could still handle these cases. In the present setup, we had more control over droplet density, and YOLO was able to detect and crop the droplets, as shown in Fig. 7a.

Moreover, the 3D position of droplets in the measurement volume across a total of 100 image recordings and the corresponding projection on the xy -plane with a colormap indicating the corresponding predicted diameters are shown in Fig. 7 c and d.

Since a direct assessment of the predicted values in the experimental case of spray droplets is not possible because the ground-truth values are not available, we proceeded with a statistical evaluation of the results. We analyzed the histogram of the detected positions and diameters of droplets, and the results are presented in Fig. 8. Fig. 8a and b show the distribution of the x and y positions of the detected droplets. In-plane (xy) detection is done by YOLO, and a comparison between the expected uniform distribution in the circular area (dashed red line) and the predicted positions shows excellent agreement. Fig. 8c and d illustrate the histogram of the variables z and

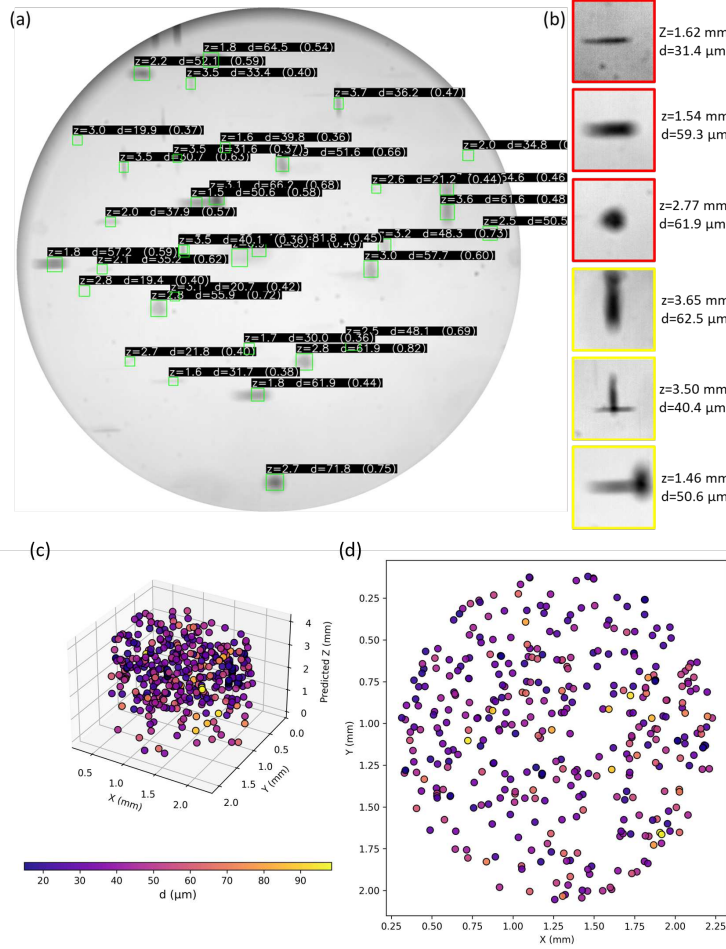


Fig. 7 a) Sprayed droplets detected by YOLO, b) VGG16 z and d prediction in single (red border) and overlapped (yellow border) droplets, c) 3D view of detected sprayed droplet positions and related diameter in the colorbar, d) XY plane projection.

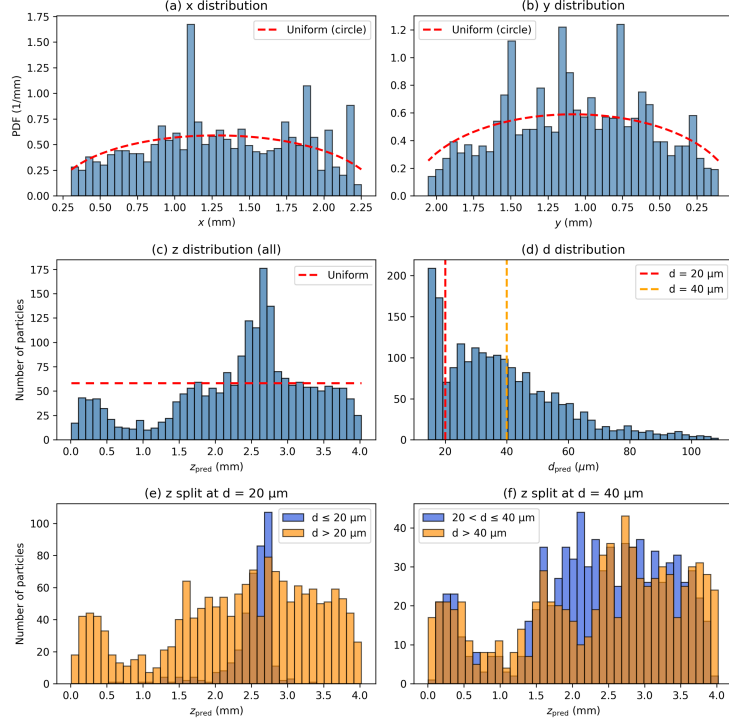


Fig. 8 a) and b) Histogram of x and y positions of detected spray droplets and histogram of uniform particle distribution. c) and d) Histogram of depth position and predicted diameter of detected droplets. e) Histogram of predicted z values for particles bigger and smaller than $20\text{ }\mu\text{m}$ and f) particles with diameter of $20 < d < 40\text{ }\mu\text{m}$ and $d > 40\text{ }\mu\text{m}$.

d , which are predicted by the modified VGG16. The expected distribution of the depth coordinate z across the measurement volume should be constant, since we are observing a small portion of the spray where the droplet concentration is expected to be nearly homogeneous. However, Fig. 8c shows a pronounced peak in the droplet count for $2.5 < z < 2.8\text{ mm}$, together with a low count for $z < 1.5\text{ mm}$. The origin of the peak is evident if we separate the droplets with a diameter larger than $20\text{ }\mu\text{m}$ from the smaller ones, as shown in Fig. 8e. The peak is almost entirely associated with the droplets smaller than $20\text{ }\mu\text{m}$, which are detected by YOLO but outside of the depth range covered by the training of the regression model. After excluding them, the histograms for droplets below and above the cutoff diameter of $d = 40\text{ }\mu\text{m}$, become similar, as shown in Fig. 8f, with a rather uniform distribution in the range of $1.5 < z < 4\text{ mm}$. The deficit in droplet counts for $0.5 < z < 1.5\text{ mm}$ is less straightforward to explain, but is most likely attributable to one of two effects: (i) reduced detection performance of the YOLO network for highly defocused particle images with low signal-to-noise ratio (SNR) or (ii) an inaccuracy in the optical model in these regions, as also observed for the case of Synth2 dataset. Finally, the distribution of particle diameters is shown in Fig. 8d. After excluding droplets with diameters below $20\text{ }\mu\text{m}$, the distribution exhibits a positively skewed shape with a peak around $d \approx 35\text{ }\mu\text{m}$,

which is reasonably close to the nominal value reported by the manufacturer (25 μm) and qualitatively consistent with the log-normal or Rosin–Rammner distributions commonly reported for atomized sprays [38].

4 Conclusions

In this work, we presented a single-camera methodology for the simultaneous determination of 3D position and diameter of spray droplets that combines astigmatic shadowgraphy with a deep learning-based image analysis. The astigmatic defocus is obtained by placing a cylindrical lens in front of the camera objective and can be easily integrated into a commercial shadowgraphy system. The deep learning framework is a two-stage CNN pipeline consisting of a YOLO network for droplet detection and localization, and a modified VGG16 network for estimating the droplet depth position and diameter. The methodology was implemented on a commercial shadowgraphy system and it was able to detect 3D position and diameter of spray droplets with diameters ranging between 20 μm and 100 μm inside a measurement volume of $2.7 \times 2.3 \times 4.0 \text{ mm}^3$.

A key aspect of the proposed approach is that both networks were trained exclusively on synthetic images generated using a computationally inexpensive Gaussian-based optical model. The synthetic model relies on a few parameters that can be easily adjusted to fit reference images obtained using the optical arrangement in use. Despite the simplicity of the image formation model, the trained networks generalized successfully to unseen synthetic images generated with ray-tracing, and unseen experimental images acquired with the same optical setup. The diameter determination remained consistently reliable across the measurement volume with uncertainty around 2.1–2.4 μm . Some limitations in the depth determination were observed in the boundary region of the measurement depth, where the optical model is not so accurate due to stronger aberrations or low SNR. Future work will be focused on improving the optical models or testing alternative optical arrangements, such as double refraction of birefringent crystals [39].

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