

Application of Micro-PIV for the Investigation of Evaporation-Driven Flow Inside a Microdroplet

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ABSTRACT

Evaporation-driven flow inside sessile microdroplets governs transport, deposition, and drying in inkjet printing, coating, biochemical analysis, and microfluidic handling. Micro-particle image velocimetry (Micro-PIV) can measure these flows, but conventional side view measurements are constrained by optical distortion near the curved droplet interface. Ray tracing correction can map visible vectors back to physical coordinates, yet peripheral regions and low contact angle stages often suffer from particle image loss or severe blur. Here, an extended Micro-PIV framework combines side view reference measurements with a bottom view two-dimensional, three-component (2D-3C) reconstruction method. The bottom view method keeps the robust in-plane velocity measurement of cross-correlation PIV and estimates the out-of-plane velocity component from particle image appearance changes. Representative bottom view measurements assemble xy velocity, signed z velocity, and 2D-3C vectors on single measurement planes and across stacked substrate referenced depth slices. In the central droplet region, the reconstructed circulation is qualitatively consistent with the side view reference trend: recirculating flow weakens during evaporation and the apparent vortex region shifts downward. In the edge region, where side view Micro-PIV becomes unreliable, the bottom view reconstruction provides access to previously obscured flow features and indicates an additional upper circulation with weak upward velocity components near the lower edge. Together, the central and edge measurements extend Micro-PIV toward optically difficult regions of evaporating microdroplets and identify particle-wise depth estimation as a feasible approach for bottom view 2D-3C droplet flow measurement.

1. Introduction

Sessile droplet evaporation is a canonical microscale transport problem with direct relevance to inkjet printing, coating, biochemical analysis, and particle deposition control. The final deposition pattern can be governed by internal liquid motion as much as by the net evaporation rate. The coffee ring mechanism identified by Deegan et al. (1997), subsequent analyses of evaporating sessile drop flow (Hu & Larson, 2005), and recent reviews of inkjet and droplet fluid dynamics

challenges (Lohse, 2022) all emphasize that quantitative flow data are essential for understanding and controlling these systems. For binary or multicomponent droplets, the problem becomes more complicated because preferential evaporation couples concentration gradients, Marangoni stress, natural convection, and changing droplet geometry (Diddens et al., 2021).

Particle image velocimetry (PIV) and Micro-PIV provide established tools for measuring flow in small liquid volumes (Adrian, 1991; Willert & Gharib, 1991; Meinhart et al., 1999; Raffel et al., 2018). In the authors' previous Micro-PIV workflow, particle images were acquired in a side view cross section of an evaporating sessile droplet, droplet geometry was extracted by a U-Net-based image analysis pipeline, and cross-correlation PIV was combined with ray tracing correction to compensate for the droplet lens effect (Kang et al., 2004; Ronneberger et al., 2015; Cong et al., 2025a,b, 2026). That workflow provides reliable velocity fields in the optically accessible region and has been used to characterize evaporation-driven recirculating flow in glycerol-water mixture droplets. However, side view Micro-PIV has a structural limitation: when the droplet interface refracts or reflects the illumination strongly, the particle image near the droplet edge can be lost before any postprocessing correction can recover it. This limitation becomes especially restrictive as the contact angle decreases and the measurable clear region shrinks.

Volumetric approaches such as tomographic PIV can reconstruct three-dimensional velocity fields from multi-camera particle images (Elsinga et al., 2006; Scarano, 2012). In the present evaporating droplet configuration, however, applying tomographic PIV would be difficult because the evolving curved liquid-air interface strongly complicates optical access, ray path modeling, and multi-camera calibration.

In parallel, machine learning has become a practical component of fluid mechanics measurement and modeling workflows (Raissi et al., 2019; Brunton et al., 2020). For image based experiments, the most useful role of machine learning is often not to replace the measurement principle, but to extract information from image features that are difficult to describe analytically. In the present study, this idea is applied to particle images recorded from the bottom view of a droplet. The in-plane velocity components remain well suited to standard cross-correlation PIV, while the out-of-plane displacement is inferred from local particle image appearance changes using a supervised depth difference model.

The present study develops an extended Micro-PIV method for measuring internal flow during microdroplet evaporation. The framework uses the side view method as a qualitative reference in the central measurable region and introduces a bottom view 2D-3C method that estimates all three velocity components on planar measurement grids. The term 2D-3C is used here in the conventional sense of a two-dimensional spatial sampling plane with three velocity components; it is not yet a full volumetric 3D-3C measurement. The main technical contribution is the particle-wise depth difference model and its integration into a bottom view velocity processing pipeline. The method is evaluated through a single plane reconstruction example, a qualitative central re-

gion comparison with the side view trend, and an edge region measurement where the side view method is optically limited.

2. Methodology

2.1. Experimental setup and side view reference method

The baseline measurement method follows the Micro-PIV workflow reported by Cong et al. (2026). Illumination was provided by a laser source (Bioray 520 nm, 50 mW elliptical dot diode laser) shaped with cylindrical lenses. Both imaging branches used cameras (Basler a2A1920-160umBAS). The side view branch used an objective lens (Mitutoyo M Plan Apo 10 $\times$), while the bottom view branch used an objective lens (Mitutoyo M Plan Apo SL 20 $\times$) mounted above the beam-splitting cube. The fluorescence imaging path used a long-pass filter and a dichroic mirror with cutoff wavelengths of 550 nm. Fluorescent particles with a diameter of 0.3 μm were seeded in the working fluid. Sessile microdroplets were generated on a hydrophobic substrate and allowed to evaporate in a controlled chamber. In the side view reference measurement, particle images were acquired in a cross section of the droplet, while shadowgraph information was used to track the evolving droplet interface. The optical layout used for the side view reference path and the bottom view measurement path is summarized in Figure 1.

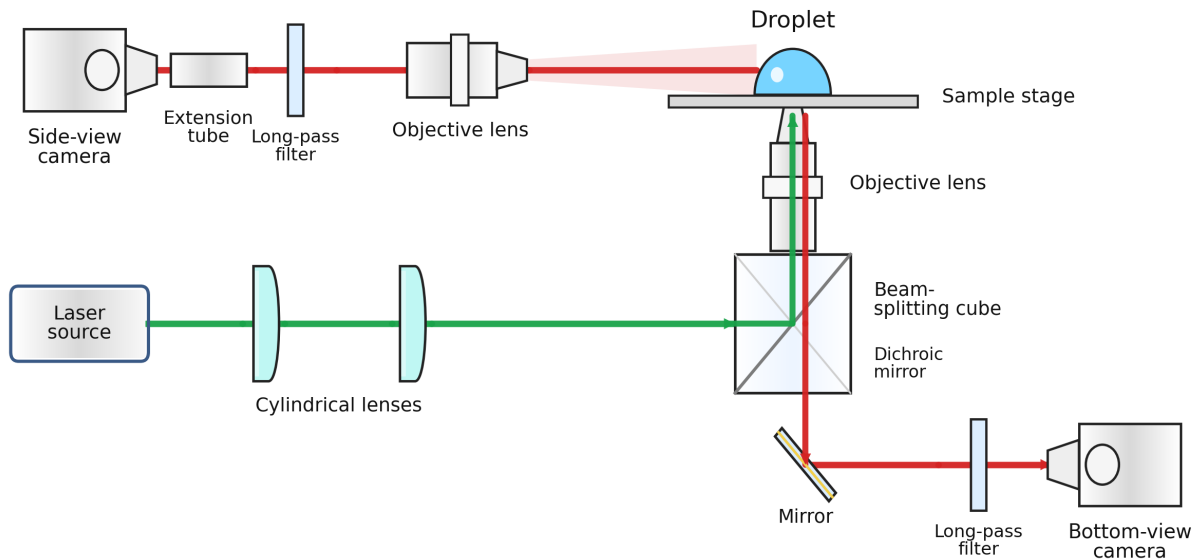


Figure 1. Schematic of the combined optical arrangement. Starting from the side view configuration, the platform can be reconfigured for bottom view measurement by installing an additional objective lens above the beam-splitting cube.

The side view data processing chain consists of four steps. First, droplet geometry is extracted

from particle images using a trained U-Net segmentation model (Ronneberger et al., 2015). Second, the droplet region of interest is cropped according to the detected interface. Third, conventional cross-correlation PIV is applied to obtain a two-component velocity field in the imaging plane. Fourth, the measured field is mapped back to physical coordinates using ray tracing correction following the lens effect correction concept of Kang et al. (2004). In regions where particles are sharply imaged, this method gives robust velocity vectors and is treated here as the reference measurement.

The limitation is optical coverage rather than only geometric distortion. Figure 2 summarizes the role and limitation of the side view correction. Before correction, the vectors are expressed in the optically distorted image coordinates. Ray tracing correction maps the visible vectors back to physical coordinates and improves the interpretation of the central measurable region. However, the correction can only act on particle images that remain measurable. In the near-interface annular region, particle images are often lost, blurred, or mixed with reflection artifacts before the PIV and correction steps. This region is therefore the main target for the bottom view measurement.

The two views were acquired separately in the present study because their optical requirements are different. The side view reference uses laser sheet illumination to isolate a cross sectional plane, whereas the bottom view method relies on illumination of the observed droplet volume so that particle image defocus can carry depth information. After the bottom view objective lens is installed above the beam-splitting cube, the cylindrical lens arrangement can be adjusted to illuminate the observed droplet volume rather than forming the side view laser sheet. The two configurations therefore use the same laser source but different illumination geometries, laser output settings, and particle image conditions. A simultaneous side view and bottom view experiment would therefore require a redesigned optical arrangement and matched seeding/illumination conditions, and it was not used for the present comparison dataset.

2.2. Bottom view 2D-3C reconstruction and depth estimation

The proposed bottom view method combines two velocity estimation operations. The in-plane components (u, v) are obtained from successive bottom view frames using a conventional cross-correlation PIV algorithm. The out-of-plane component w is obtained by estimating signed depth difference from particle image appearance changes, so that motion in both positive and negative z directions can be represented. The physical z coordinate is defined as positive away from the substrate. The reconstructed result is expressed as a 2D-3C velocity field on droplet depth slices, with local particle support information retained for masking and filtering. The reported velocities are expressed in $\mu\text{m s}^{-1}$.

For a video sequence, pairs of frames are selected using prescribed time intervals Δt_{xy} for in-plane PIV and Δt_z for depth estimation. The in-plane PIV displacements are first converted from pixels

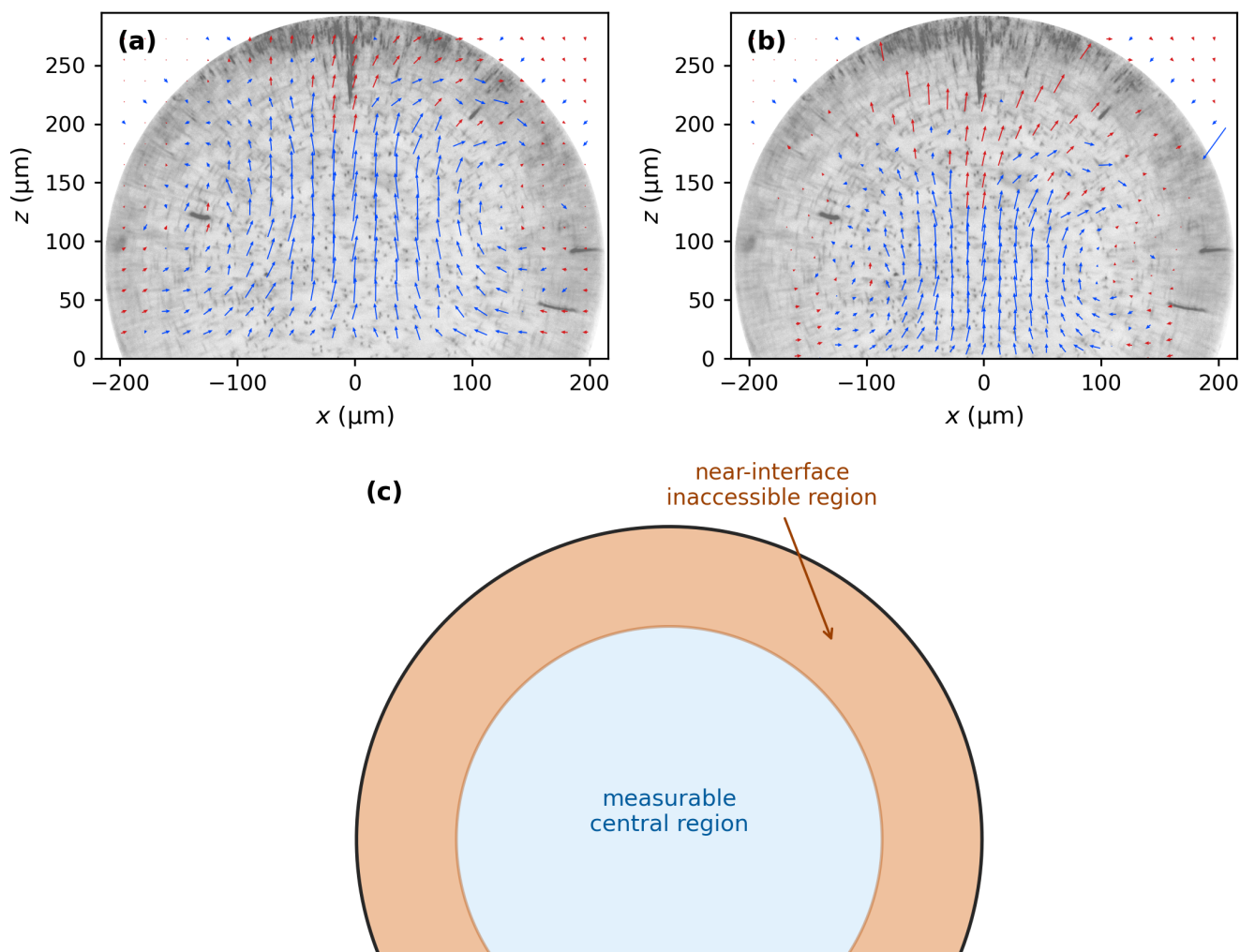


Figure 2. Role and limitation of side view lens effect correction. (a) PIV vectors before correction. (b) Corrected vectors after ray tracing correction for visible particle images. Blue vectors are retained after quality control, while red vectors are rejected or unreliable. (c) Schematic indication of the near-interface annular region where particle images are strongly degraded and vectors cannot be reliably recovered.

to micrometers using the image calibration, while the depth model output is already expressed in micrometers because it is trained on commanded focal-plane depth differences. The depth model predicts a signed focal-plane-equivalent displacement Δz_{model} . With the calibration convention used here, this model displacement has the opposite sign to the physical particle displacement along z . The displacement estimates are therefore converted to velocity components as

$$u = \frac{\Delta x}{\Delta t_{xy}}, \quad v = \frac{\Delta y}{\Delta t_{xy}}, \quad w = -\frac{\Delta z_{\text{model}}}{\Delta t_z}. \quad (1)$$

In the present processed results, representative bottom view runs used 50 fps videos, 128 pixel interrogation windows, and time intervals of 0.1 s or 0.2 s depending on the result set. The same processing can be applied to each selected measurement plane, giving planar 2D-3C velocity fields that can later be stacked for visualization of the measured droplet region.

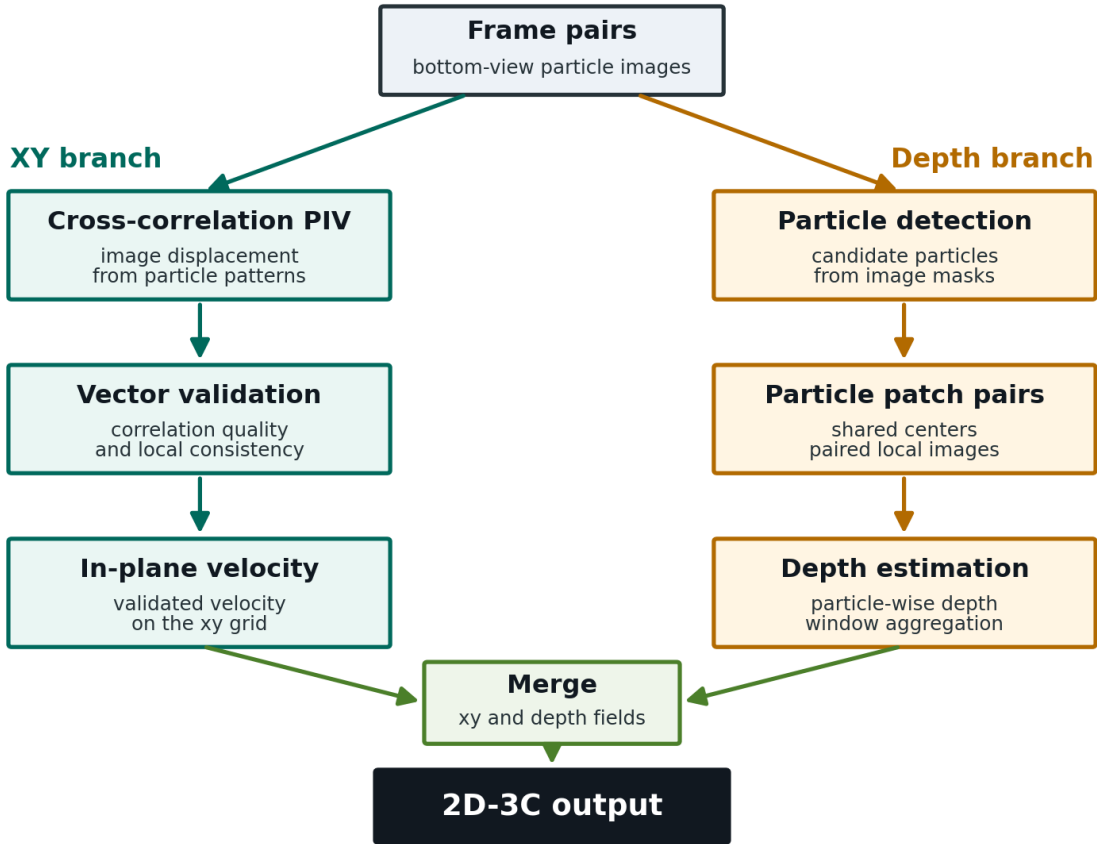


Figure 3. 2D-3C Micro-PIV processing workflow. Frame pairs are processed by an xy PIV branch and a depth estimation branch, then merged into a three-component velocity field.

The depth estimator was designed for image pairs in which the useful information is carried by the local defocused particle image rather than by a globally smooth texture. Each input frame is converted to a normalized single channel intensity image, and particle-like components are extracted

using simple intensity and size filtering. Component centroids are then obtained by connected component labeling (Rosenfeld & Pfaltz, 1966). For an image pair, centers from both frames are pooled into a shared set before patch extraction. This shared center strategy preserves particle coverage in both frames and avoids the coverage loss observed when a strict one to one particle matching step is used.

For every merged particle center (x_i, y_i) , two square patches are cropped from the two frames by reflection padding:

$$p_i^{(1)} = I^{(1)}[x_i, y_i; P], \quad p_i^{(2)} = I^{(2)}[x_i, y_i; P], \quad (2)$$

where $I[x_i, y_i; P]$ denotes a square crop of side length P centered at (x_i, y_i) in image coordinate notation. Particle predictions are then aggregated on an overlapping window grid to obtain local focal-plane-equivalent displacement estimates. The key preprocessing and aggregation settings used in this study are summarized in Table 1. Figure 4 shows the same preprocessing sequence for denser and sparser calibration image pairs. The denser case retains more particle centers in the selected region, but the paired patches also show stronger background texture and particle image interference, which makes the supervised depth difference problem less clean than in the sparser case.

Table 1. Key particle preprocessing and aggregation settings used for the depth difference model.

Item	Value	Purpose
Intensity threshold	0.18	Particle mask generation
Component area range	20-500 pixels	Particle-like component selection
Center merge distance	8 pixels	Shared center construction
Patch size P	32 pixels	Local particle image representation
Maximum particles per pair	512	Batch size control
Aggregation window / stride	128 / 64 pixels	Local model displacement aggregation

The network follows a Siamese design (Bromley et al., 1993): the two particle patches share the same convolutional encoder, so the two images are represented in a common feature space. The encoder maps each particle patch to a compact feature vector using a sequence of convolutional blocks followed by global pooling and a linear projection, as shown in Figure 5:

$$h_i^{(1)} = E(p_i^{(1)}), \quad h_i^{(2)} = E(p_i^{(2)}). \quad (3)$$

The pair descriptor combines both absolute and relative feature information,

$$g_i = [h_i^{(1)}, h_i^{(2)}, h_i^{(2)} - h_i^{(1)}, |h_i^{(2)} - h_i^{(1)}|, h_i^{(1)} \odot h_i^{(2)}], \quad (4)$$

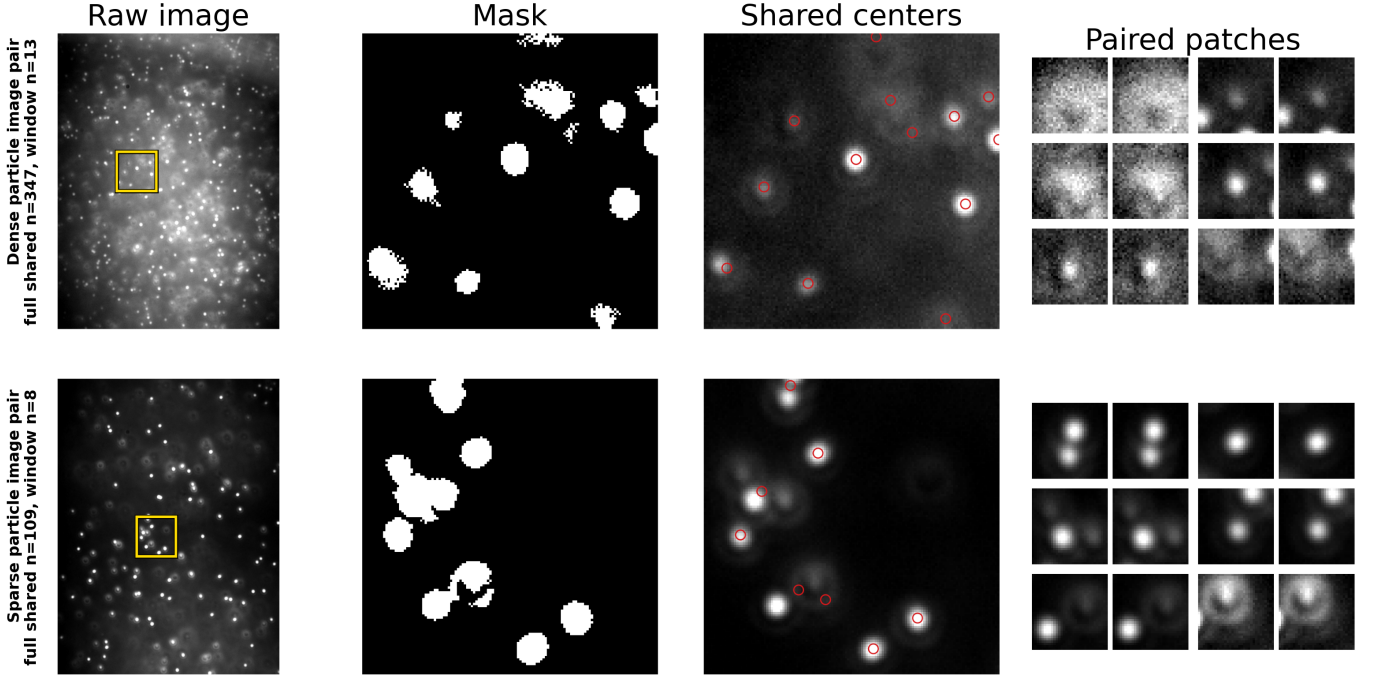


Figure 4. Particle preprocessing used by the depth difference model for denser and sparser calibration image pairs. The panels show the raw image, binary particle mask, shared center locations, and example paired particle patches.

and is passed to a multilayer prediction head. The head outputs a particle level focal-plane-equivalent displacement estimate δ_i and a learned aggregation weight $c_i \in [0, 1]$. The weight is used only for local window aggregation and is not interpreted as calibrated confidence or uncertainty. Here, $|\cdot|$ is applied element-wise and $\odot$ denotes element-wise multiplication.

For each aggregation window j , let $\mathcal{W}_j$ denote the set of valid particles whose centers lie inside the window. The local model displacement is aggregated by learned weighting:

$$\Delta z_{\text{model},j} = \frac{\sum_{i \in \mathcal{W}_j} c_i \delta_i}{\sum_{i \in \mathcal{W}_j} c_i + \epsilon}, \quad (5)$$

where ϵ is a small constant used only for numerical stability. The retained support variable is the number of valid particles contributing to each aggregation window. Windows without valid particles are excluded from the supervised loss and masked during inference, so the minimum retained support for displayed depth estimates is one valid particle per window. This support mask is separate from the learned aggregation weight c_i .

2.3. Training and calibration model selection

The supervised depth difference dataset was collected from a pure glycerol droplet. Pure glycerol was used because its high viscosity strongly suppresses internal flow during the acquisition, so

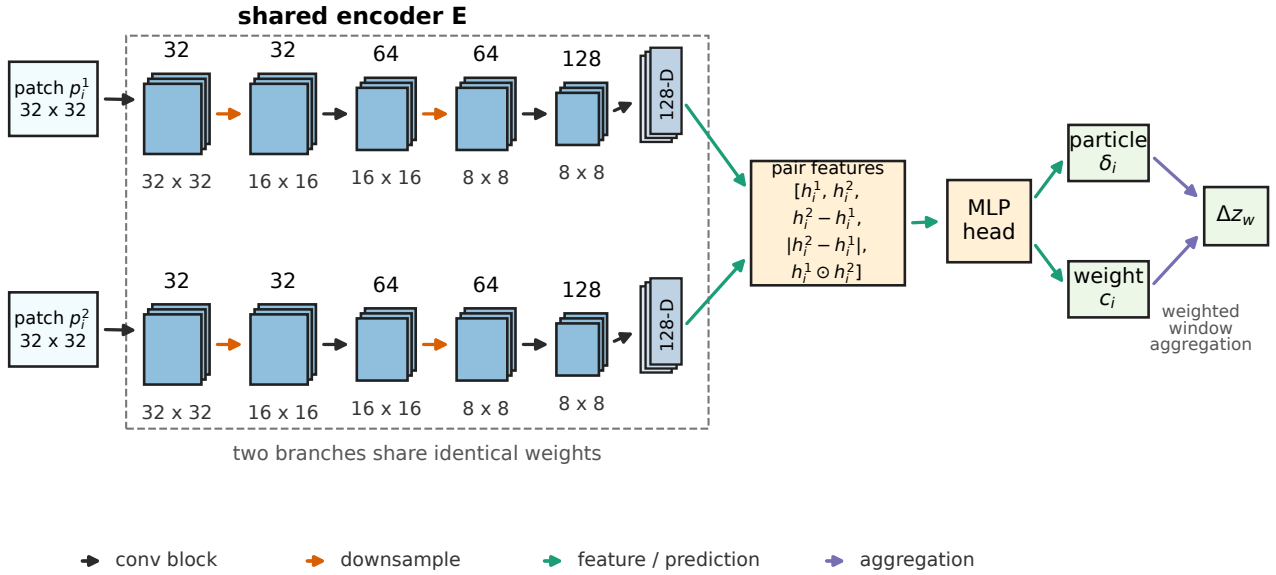


Figure 5. Schematic of the particle-wise depth difference model from paired particle patches to local window estimates.

changes in particle appearance are dominated by controlled focal displacement rather than by real particle transport. Known focal-plane depth differences were introduced by moving the imaging plane with a piezo inertia actuator (Thorlabs PIA13, 13 mm travel). The commanded depth differences were expressed in micrometers and used as the supervised depth difference labels.

The model was implemented in PyTorch (Paszke et al., 2019) and optimized with Adam (Kingma & Ba, 2014). Training used supervised image pairs with signed focal-plane-equivalent labels and a staged curriculum from small to full range displacement magnitudes. The training pairs covered both positive and negative focal-plane-equivalent displacements within the selected depth difference range. The loss combined window and particle supervision,

$$\mathcal{L} = \mathcal{L}_{\text{window}} + 0.2 \mathcal{L}_{\text{particle}}, \quad (6)$$

where the target assigned to each valid window was the known signed depth difference of the image pair. Here, $\mathcal{L}_{\text{window}}$ is the mean absolute error between the aggregated window displacement and the signed calibration label, and it is the primary loss used for model selection. The auxiliary term $\mathcal{L}_{\text{particle}}$ applies the same signed label to valid particle level estimates δ_i within the training pair, encouraging the local patch predictions to remain physically consistent before window aggregation. The main training settings are summarized in Table 2.

Small in-plane particle motion can mimic a depth dependent point spread function change. This effect is expected in real droplet measurements because particles can translate between frames, the detected center can shift slightly with defocus and background variation, and Brownian-like

Table 2. Key training settings for the selected depth difference model.

Item	Setting
Optimizer	Adam
Learning rate	10^{-3}
Batch size / accumulation	4 / 2 steps
Precision	bfloat16 mixed precision
Depth curriculum	staged from adjacent levels to full range
Loss weighting	window loss + 0.2 particle loss
Selected training jitter	± 4 pixels

irregular motion can perturb the local image patch. The final method therefore kept shared particle centers and applied independent random crop jitter to the two patches during training only. The validation and inference pipelines remain deterministic with no jitter. A jitter range of ± 4 pixels gave the best completed full range result.

Table 3 summarizes the calibration dataset comparison used to select the application model. The sparser particle dataset gave the lowest numerical error, with a window MAE of $0.2450\ \mu\text{m}$ and about 127 valid particles per image pair. The denser particle dataset increased the mean valid particle count to about 423, but its baseline window MAE increased to $0.3817\ \mu\text{m}$. This degradation is consistent with the more complex image background and stronger particle image interference visible in the denser paired patches in Figure 4. Nevertheless, the denser setting is the more relevant basis for the bottom view application because real measurements require a high particle concentration to provide sufficient window support across the droplet.

Within the denser dataset, xy jitter during training was introduced to make the particle patch model less sensitive to small in-plane particle displacement, center detection error, and irregular particle motion between frames. A jitter range of ± 4 pixels reduced the window MAE from $0.3817\ \mu\text{m}$ to $0.3678\ \mu\text{m}$ while retaining the same particle coverage. Increasing the jitter to ± 6 pixels gave a nearly identical but slightly worse window MAE, suggesting that stronger jitter can begin to remove useful local particle shape information.

Because the training labels are commanded focal-plane depth differences in micrometers, the MAE values are reported as equivalent depth errors in micrometers for the controlled calibration dataset. In the manuscript, these values are used primarily for relative selection among model variants before application to flowing droplets. The window MAE in Table 3 is the validation error after learned weight aggregation and is the metric used for model selection. The particle MAE is retained only as a diagnostic for the auxiliary particle level prediction.

The main empirical conclusion is that lower particle density can give a cleaner supervised depth

Table 3. Calibration dataset model selection results for signed focal-plane-equivalent displacements with magnitudes from 0 to 5 μm . The MAE values are equivalent depth errors in micrometers for the controlled calibration dataset; the sparser and denser datasets differ in particle concentration and background complexity, and all denser variants use the same 128 pixel window protocol.

Model variant	Window MAE [μm]	Particle MAE [μm]	Valid particles
Sparsar ParticlePatch baseline	0.2450	0.5079	127.27
Denser ParticlePatch baseline	0.3817	0.9680	423.36
Denser shared center + 2 px training jitter	0.3904	0.9463	423.36
Denser shared center + 4 px training jitter (selected)	0.3678	0.9387	423.36
Denser shared center + 6 px training jitter	0.3684	0.9349	423.36

estimation problem, but the application constraint favors the denser training condition. The final architecture therefore learns particle-wise depth differences from paired local patches under denser particle conditions and uses xy jitter during training to prevent small in-plane crop offsets from being learned as depth differences.

3. Results and Discussion

The representative droplet measurements discussed in this section were obtained using a 20% glycerol aqueous solution. The droplet radius was approximately 190 μm , and the initial contact angle was approximately 115° . The ambient temperature was maintained at about 25°C , while the relative humidity was in the range of 40-60%. For the bottom view reconstructions, seven substrate referenced measurement planes from 10 to 130 μm were processed as droplet depth slices. These slices were acquired from controlled condition droplet experiments at different measurement plane settings, rather than from a single instantaneous volumetric scan of one droplet.

3.1. Single plane bottom view reconstruction

The bottom view pipeline was first examined on a single measurement plane to clarify how the three velocity components are assembled. Figure 6 shows an example from the substrate referenced 30 μm depth slice at $t = 20$ s. The in-plane PIV branch provides the x - y velocity vectors, while the depth model provides the local signed z component map. In this plotted map, the color value follows the model-output sign convention; negative plotted values correspond to positive physical w after the sign conversion in Eq. (1). Combining these two outputs gives a local 2D-3C representation of the selected droplet depth slice. A particle support mask is also applied: depth estimation windows with zero valid particles are not interpreted as measured z velocities, and retained windows have at least one contributing particle.

The same operation was repeated at the selected substrate referenced depth slices. A representative

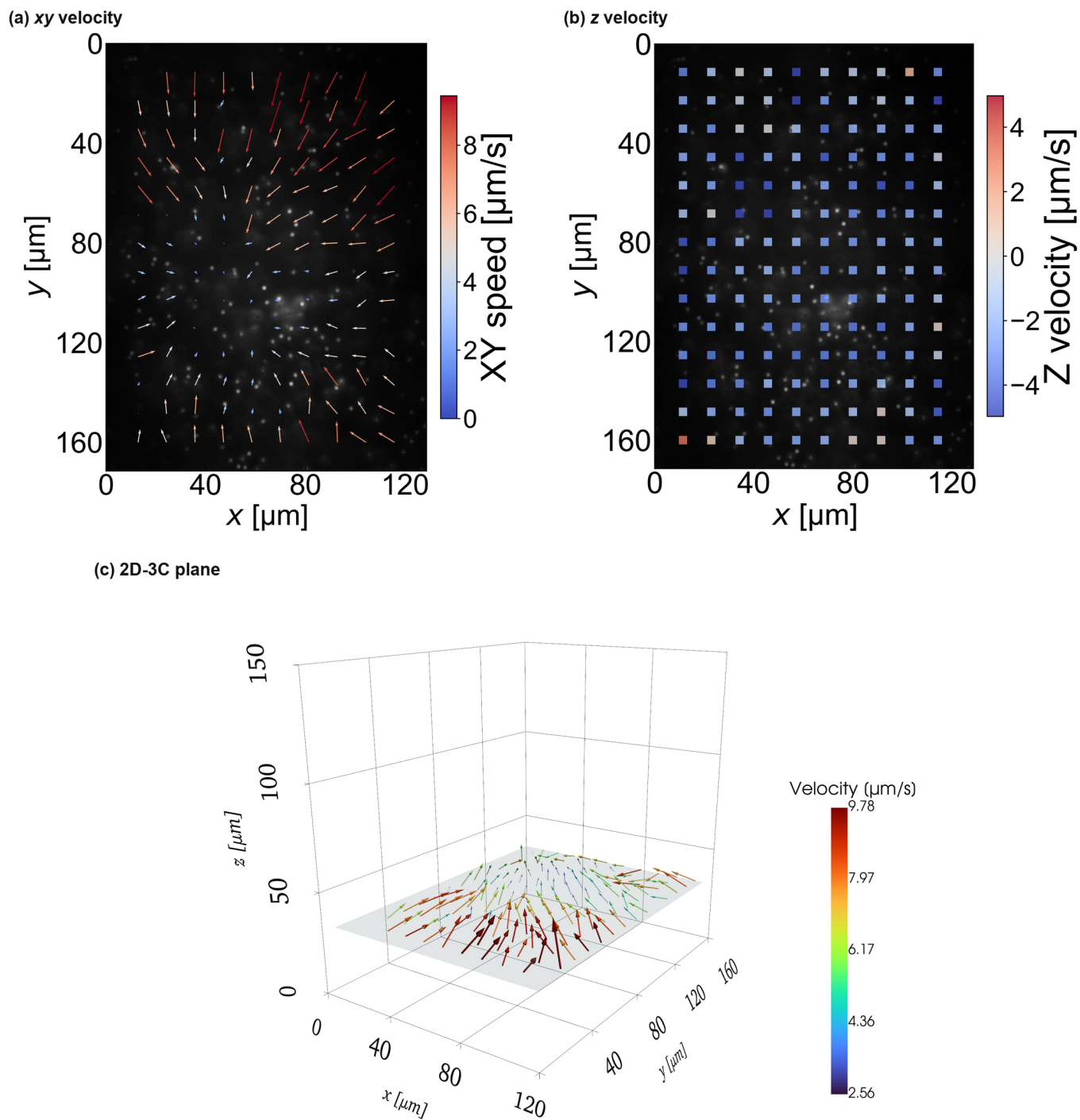


Figure 6. Single plane bottom view reconstruction example at the 30 μm depth slice and $t = 20$ s. (a) In-plane velocity from the xy PIV branch. (b) Signed z component from the depth difference branch, plotted using the model-output sign convention. (c) Combined 2D-3C velocity field for the same plane.

stacked reconstruction is shown in Figure 7. This view illustrates how independently processed planar 2D-3C fields can be assembled into an overall three-dimensional visualization of the measured droplet region. The result should still be interpreted as a stack of controlled measurement planes, not as an instantaneous volumetric scan of one single droplet.

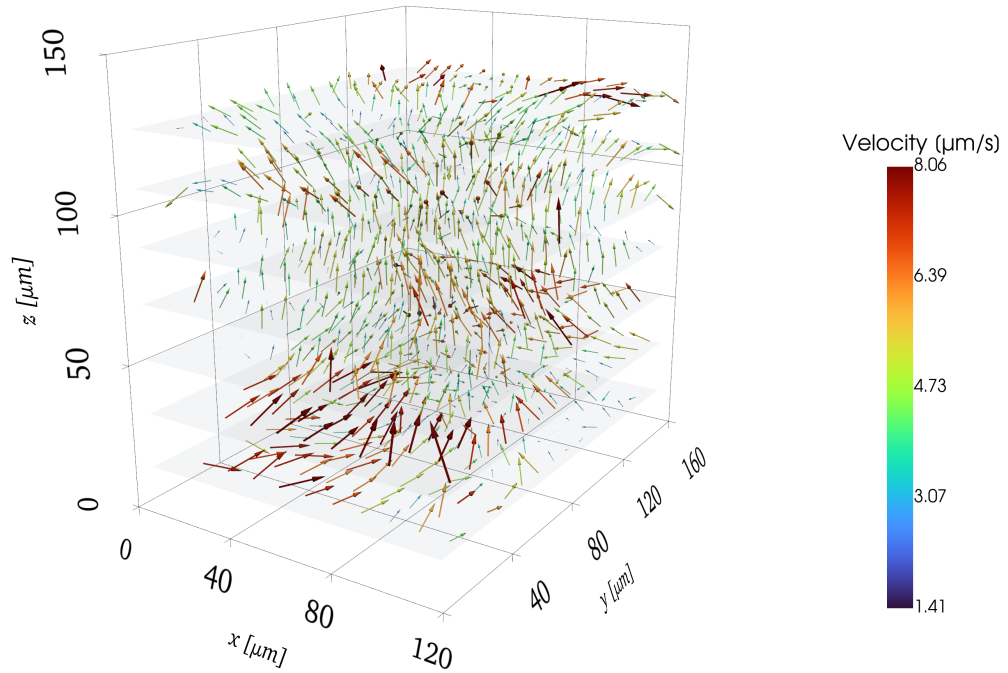


Figure 7. An example of stacked 2D-3C reconstruction for the central measurement region at $t = 25$ s. The displayed field combines the processed droplet depth slices measured from the substrate.

3.2. Qualitative comparison with the side view trend

Figure 8 shows the side view reference field in the optically measurable region. The corrected vectors reveal a recirculating internal flow, but the measurable region is limited because the curved interface degrades the particle images near the droplet edge. The overlaid bands indicate the bottom view sampling locations used later for the middle and edge reconstructions. Each band is $120\ \mu\text{m}$ wide in the x direction, while its full-height display is only a visual location guide rather than a physical z direction measurement range. The side view data therefore provide a qualitative reference for the central region rather than a pointwise three-dimensional validation target.

The central bottom view sequence in Figure 9 corresponds to the middle sampling location indicated in Figure 8 and shows a similar bulk circulation pattern in the accessible region. During the

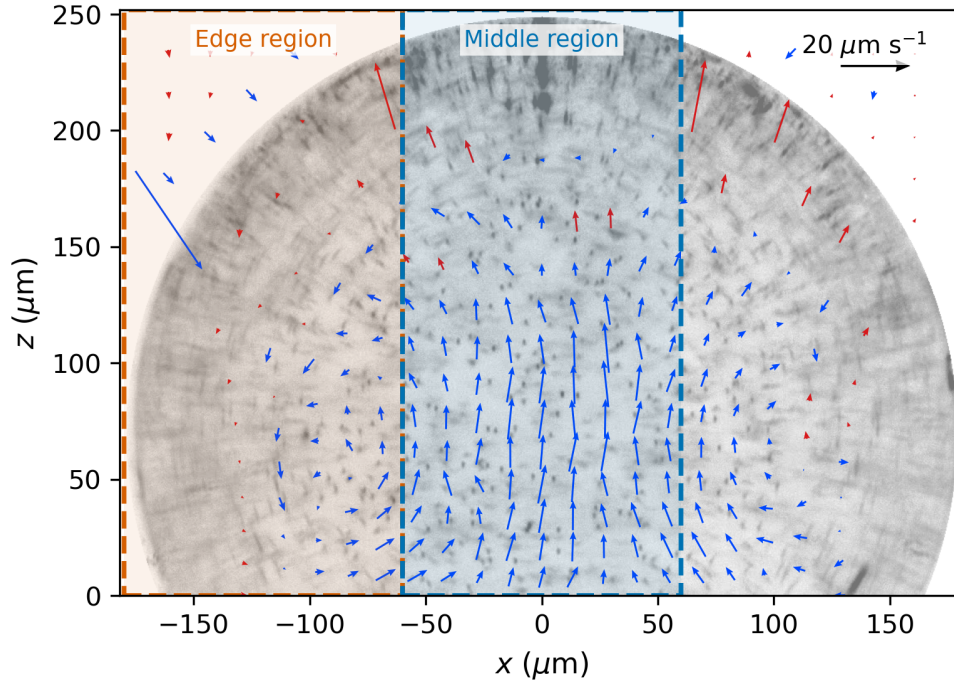


Figure 8. Representative side view Micro-PIV result after lens effect correction in the optically measurable region. Blue vectors denote vectors retained after quality control, while red vectors denote rejected or unreliable vectors. The blue and orange outlined bands indicate the middle and edge bottom view sampling locations, respectively.

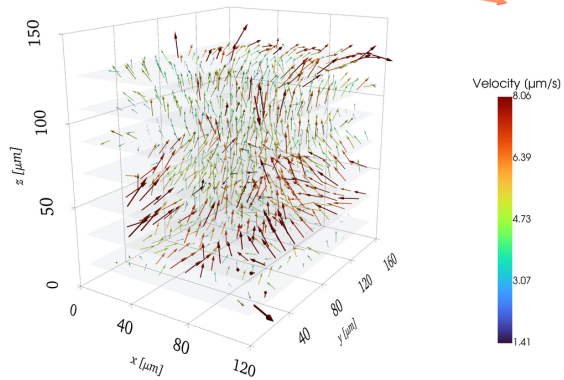
early stage, the vortex center is located around the middle of the droplet height, near $z = 75 \mu\text{m}$. As evaporation proceeds, the circulation becomes progressively weaker and the apparent vortex region shifts downward. This trend is consistent with the side view observation that the initially clear recirculating flow is gradually suppressed and finally becomes weak. Because the side view and bottom view measurements were not synchronized measurements of the same droplet, the comparison is interpreted qualitatively. Within that limitation, the agreement in flow structure, velocity scale, and temporal weakening indicates that the bottom view 2D-3C reconstruction is consistent with the side view trend in the measurable central region.

3.3. Bottom view measurement near the side view inaccessible region

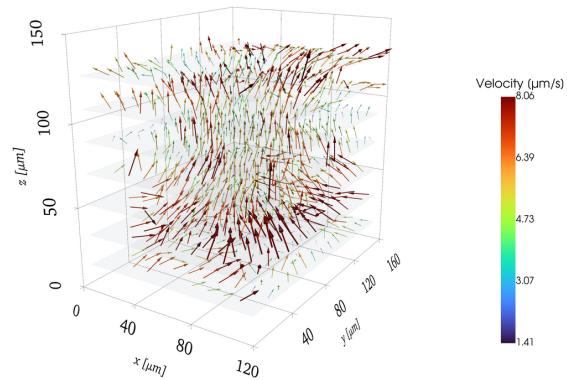
The edge region dataset was then processed using the same bottom view pipeline. This region corresponds to the edge sampling location indicated in Figure 8 and represents the main use case of the new method, because side view Micro-PIV becomes unreliable near the droplet interface. Figure 10 shows the time evolution reconstructed near this side view inaccessible region.

At the beginning of the sequence, the edge region is dominated by one large circulation structure. As evaporation proceeds, the bulk flow is suppressed and shifts downward, similar to the central region trend. At the same time, an additional circulation appears in the upper part of the

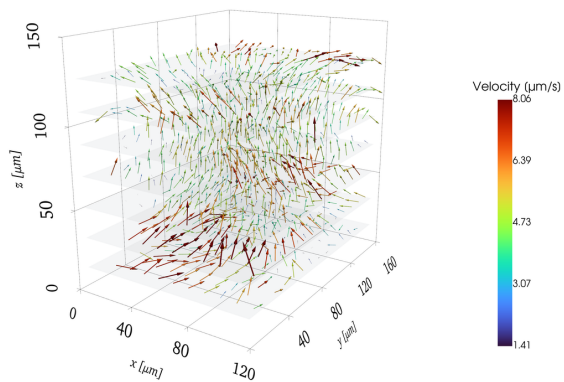
(a) $t=5$ s



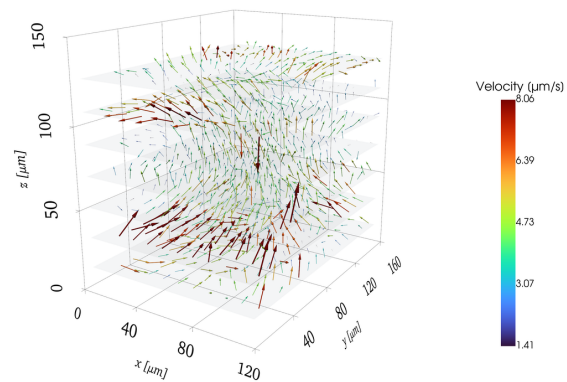
(b) $t=15$ s



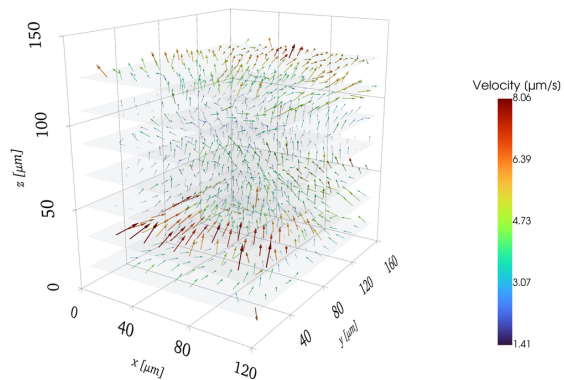
(c) $t=25$ s



(d) $t=35$ s



(e) $t=45$ s



(f) $t=55$ s

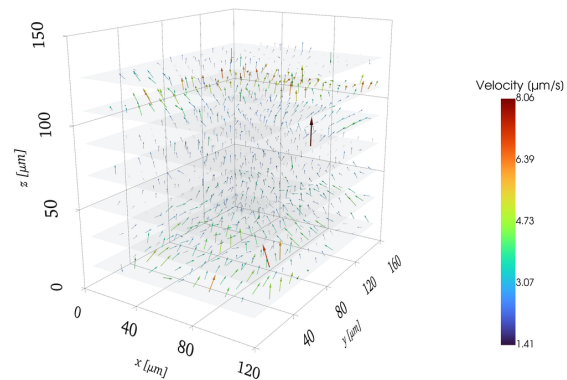
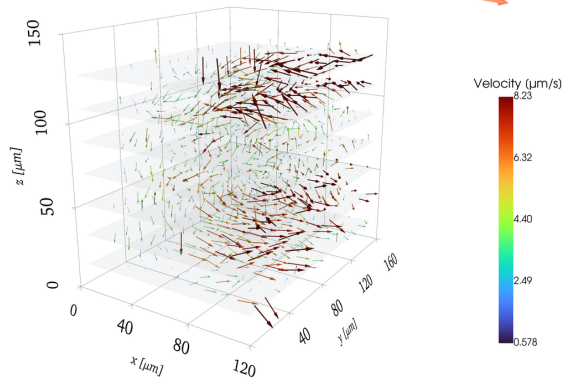
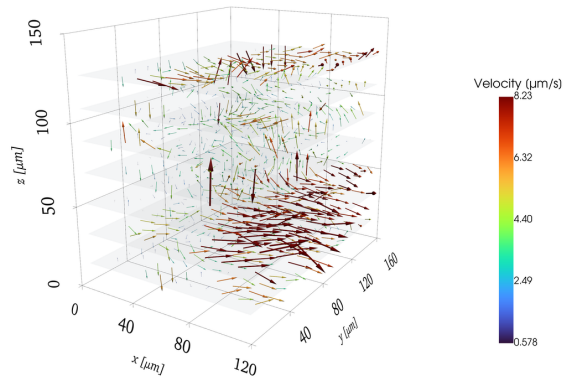


Figure 9. 2D-3C reconstruction of the central region at different evaporation times. The central region corresponds to the blue sampling band indicated in Figure 8.

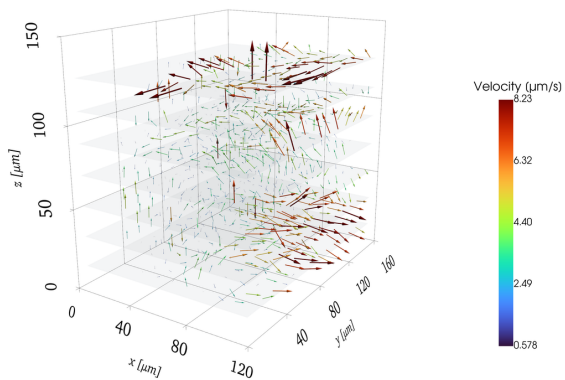
(a) $t=5$ s



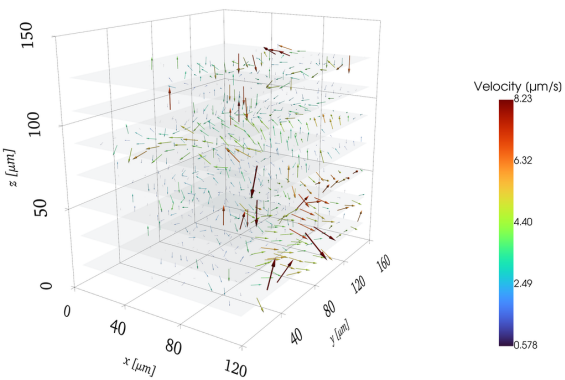
(b) $t=15$ s



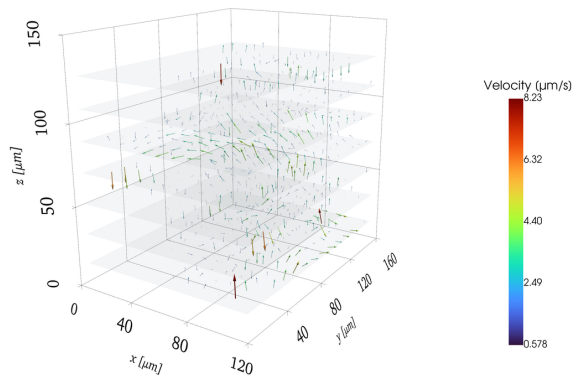
(c) $t=25$ s



(d) $t=35$ s



(e) $t=45$ s



(f) $t=55$ s

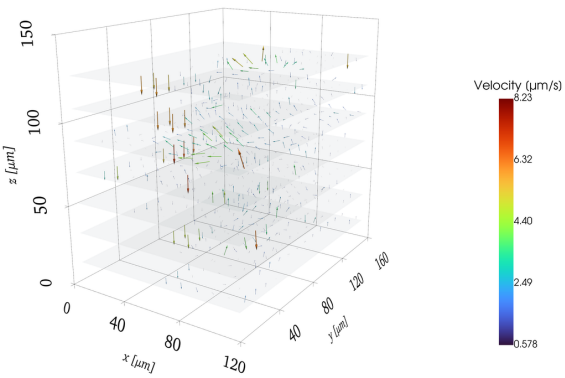


Figure 10. 2D-3C reconstruction near the edge region at different evaporation times. The edge region corresponds to the orange sampling band indicated in Figure 8.

measured region. This structure is qualitatively consistent with the competing Marangoni and Rayleigh convection picture predicted for evaporating binary droplets by Diddens et al. (2021), in which different driving mechanisms can produce competing circulation cells. The present observation should be treated as an experimental indication rather than a definitive mechanistic proof, but it is important because such an upper edge circulation is not accessible in the previous side view workflow. The edge reconstructions also show weak upward velocity components near the lower edge region, indicating that the local motion is not limited to the downward branch of the bulk circulation.

4. Conclusions

This study developed an extended Micro-PIV methodology for measuring evaporation-driven flow inside a microdroplet. The established side view Micro-PIV workflow provides reliable reference measurements in the optically accessible central region, but it is limited near the droplet interface because particle image information can be lost by the lens effect. To address this limitation, a bottom view 2D-3C PIV pipeline was developed. The in-plane components are obtained by conventional PIV, and the out-of-plane component is estimated by a particle-wise machine learning depth difference model.

The depth estimator uses particle masks, connected component centers, shared center patch extraction, a Siamese convolutional encoder, and learned weight aggregation. Calibration dataset model selection indicates a tradeoff with particle image density: the sparser dataset gave a lower window MAE of $0.2450\ \mu\text{m}$, whereas the denser baseline increased the error to $0.3817\ \mu\text{m}$ because of stronger background and particle image complexity. The denser setting was retained for application because it supplies the particle support needed in real bottom view measurements, and 4 pixel xy jitter during training reduced the denser setting window MAE to $0.3678\ \mu\text{m}$.

Representative bottom view reconstructions exhibit flow structures and velocity scales similar to the side view reference in the measurable central region. The central region sequence is consistent with the expected weakening of the circulation and the downward shift of the apparent vortex region during evaporation. In the edge region, where side view Micro-PIV is unreliable, the reconstruction indicates an additional upper circulation and weak upward velocity components near the lower edge. These results are consistent with feasible recovery of three-component flow structures in regions that were previously inaccessible, although the present comparison remains qualitative. The present work therefore provides a particle based depth estimation approach for bottom view 2D-3C droplet flow measurement. Future work will focus on independent quantitative validation of the z component under flowing droplet conditions, improved uncertainty assessment, and extension from stacked 2D-3C planes toward true scanned 3D-3C measurements.

Nomenclature

c_i	Learned particle aggregation weight [-]
E	Shared particle patch encoder [-]
g_i	Pair feature descriptor for particle i [-]
$h_i^{(1)}, h_i^{(2)}$	Encoded patch features for particle i [-]
$I^{(1)}, I^{(2)}$	Paired input image frames [-]
$\mathcal{L}$	Total supervised training loss [-]
$\mathcal{W}_j$	Valid particle set in aggregation window j [-]
P	Particle patch size [pixel]
$p_i^{(1)}, p_i^{(2)}$	Paired particle patches for particle i [-]
u, v, w	Velocity components in x, y , and z directions [$\mu\text{m s}^{-1}$]
x, y, z	Spatial coordinates [μm]
$\Delta t_{xy}, \Delta t_z$	Time intervals for in-plane PIV and depth estimation [s]
$\Delta x, \Delta y$	In-plane displacement estimates in x and y directions [μm]
Δz_{model}	Model-predicted focal-plane-equivalent displacement [μm]
$\Delta z_{\text{model},j}$	Window level model displacement estimate [μm]
δ_i	Particle level model displacement estimate [μm]
ϵ	Small numerical stabilizer [-]
$\odot$	Element-wise multiplication

References

- Adrian, R. J. (1991). Particle-imaging techniques for experimental fluid mechanics. *Annual Review of Fluid Mechanics*, 23, 261–304. doi: 10.1146/annurev.fl.23.010191.001401
- Bromley, J., Guyon, I., LeCun, Y., Sackinger, E., & Shah, R. (1993). Signature verification using a Siamese time delay neural network. In *Advances in neural information processing systems* (Vol. 6, pp. 737–744).
- Brunton, S. L., Noack, B. R., & Koumoutsakos, P. (2020). Machine learning for fluid mechanics. *Annual Review of Fluid Mechanics*, 52, 477–508. doi: 10.1146/annurev-fluid-010719-060214
- Cong, H., Fushinobu, K., & Kawaguchi, T. (2025a). Experimental study on evaporation-driven flow, evaporation rate of single evaporation multicomponent sessile droplet. In *11th international symposium on turbulence, heat and mass transfer 2025 (THMT-25)*.

- Cong, H., Fushinobu, K., & Kawaguchi, T. (2025b). Visualization of evaporation-driven flow inside an evaporating sessile droplet by means of Micro-PIV. In *21st international symposium on flow visualization (ISFV21)*.
- Cong, H., Fushinobu, K., & Kawaguchi, T. (2026). Visualization of evaporation-driven flow inside an evaporating sessile droplet by means of Micro-PIV. *Measurement Science and Technology*, 37(7), 075204. doi: 10.1088/1361-6501/ae4413
- Deegan, R. D., Bakajin, O., Dupont, T. F., Huber, G., Nagel, S. R., & Witten, T. A. (1997). Capillary flow as the cause of ring stains from dried liquid drops. *Nature*, 389, 827–829. doi: 10.1038/39827
- Diddens, C., Li, Y., & Lohse, D. (2021). Competing Marangoni and Rayleigh convection in evaporating binary droplets. *Journal of Fluid Mechanics*, 914, A23. doi: 10.1017/jfm.2020.734
- Elsinga, G. E., Scarano, F., Wieneke, B., & van Oudheusden, B. W. (2006). Tomographic particle image velocimetry. *Experiments in Fluids*, 41(6), 933–947. doi: 10.1007/s00348-006-0212-z
- Hu, H., & Larson, R. G. (2005). Analysis of the microfluid flow in an evaporating sessile droplet. *Langmuir*, 21(9), 3963–3971. doi: 10.1021/la047528s
- Kang, K. H., Lee, S. J., Lee, C. M., & Kang, I. S. (2004). Quantitative visualization of flow inside an evaporating droplet using the ray tracing method. *Measurement Science and Technology*, 15(6), 1104–1112. doi: 10.1088/0957-0233/15/6/009
- Kingma, D. P., & Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- Lohse, D. (2022). Fundamental fluid dynamics challenges in inkjet printing. *Annual Review of Fluid Mechanics*, 54, 349–382. doi: 10.1146/annurev-fluid-022321-114001
- Meinhart, C. D., Wereley, S. T., & Santiago, J. G. (1999). PIV measurements of a microchannel flow. *Experiments in Fluids*, 27, 414–419. doi: 10.1007/s003480050366
- Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., ... Chintala, S. (2019). PyTorch: An imperative style, high-performance deep learning library. In *Advances in neural information processing systems* (Vol. 32, pp. 8024–8035).
- Raffel, M., Kaehler, C. J., Willert, C. E., Wereley, S. T., Scarano, F., & Kompenhans, J. (2018). *Particle image velocimetry: A practical guide* (3rd ed.). Cham: Springer. doi: 10.1007/978-3-319-68852-7
- Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686–707. doi: 10.1016/j.jcp.2018.10.045

- Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional networks for biomedical image segmentation. In *Medical image computing and computer-assisted intervention – miccai 2015* (pp. 234–241). Springer. doi: 10.1007/978-3-319-24574-4_28
- Rosenfeld, A., & Pfaltz, J. L. (1966). Sequential operations in digital picture processing. *Journal of the ACM*, 13(4), 471–494. doi: 10.1145/321356.321357
- Scarano, F. (2012). Tomographic PIV: principles and practice. *Measurement Science and Technology*, 24(1), 012001. doi: 10.1088/0957-0233/24/1/012001
- Willert, C. E., & Gharib, M. (1991). Digital particle image velocimetry. *Experiments in Fluids*, 10(4), 181–193. doi: 10.1007/BF00190388