

On the Memory of Measurements in Spray Diagnostics

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ABSTRACT

In spray diagnostics, a measurement is typically treated as the accumulation of validated droplets until sufficient statistics of the size, velocity, flux, and derived quantities can be estimated. This view implicitly assumes that measurement is mainly a sampling process. However, if the spray or measurement context changes during acquisition, the measured sequence may retain traces of what it has previously sampled. In this sense, a measurement may have memory: the present droplet-event record can carry forward information about past event organization, alphabet occupation, and changes in the local spray state. This study investigates the memory of measurements in spray diagnostics by introducing an infodynamic framework for time-ordered droplet-event data. Each validated droplet was treated as an event carrying morphological information through its size, kinematic information through its velocity, and arrival information through its inter-arrival time. Droplet-events are mapped into a fixed quantized measurement alphabet, and sliding time windows are used to quantify the real memory trace as the mutual informature between past and future droplet-event blocks. A permutation baseline, obtained by random future-block re-pairing, is then subtracted to define a corrected memory trace that isolates the resolved event-order memory from finite-sampling and marginal-occupation effects. The framework was applied to Time-Shifting Time-Of-Flight (TSTOF) measurements of a flat-fan spray under static and dynamic operating or measurement conditions. Under stable local conditions, the corrected memory trace remains close to the finite-sampling baseline, supporting an approximately distributional-sampling interpretation at the selected alphabet resolution and memory horizon. When the injection pressure and/or measurement position varied during acquisition, the infodynamic descriptors revealed measurement morphing: changes in droplet-event diversity, alphabet redistribution, and intermittent intervals in which the event order carried predictive information beyond the permutation baseline. Therefore, the proposed approach extends the conventional spray characterization by distinguishing between repeated sampling of a local spray state and monitoring of an evolving measurement state. This makes the memory of the measurements a quantifiable diagnostic concept for non-deterministic two-phase flows.

1. Introduction

A measurement is not a static, isolated data point but a dynamic entity rich in information regarding the local and temporal organizational structure of the physical system. A single measurement, when viewed in the context of a time series, contains significant information. It is not just a value but a reflection of the system dynamics, encoding aspects of both the past and the future. In spray diagnostics, we often remain at the most basic state of retrieving mean quantities to perform parametric studies to optimize the injector design. However, all researchers recognize the complexity of the atomization process and the challenges in simulating such a two-phase flow. We rarely consider a measurement as a dynamic entity from the point of view of its amount of information or *informature* (Panão, 2025b), which is the argument for investigating the possibility of memories of measurements that open new characterization layers for understanding the role of *information*, as part of the basic structure of reality, in defining sprays as complex systems.

When dissecting a measured bit of information, James et al. (2011) pose a pertinent question: "what can we learn from just a single observation?" This question is particularly relevant to the application of single-point measurement techniques in spray diagnostics, such as the Time-Shifting Time-Of-Flight (TSTOF) technique (Schäfer & Tropea, 2014) or Laser and Phase-Doppler Interferometry (Albrecht et al., 2013), because the criteria for performing a measurement do not account for the flow's memory, but instead rely on a predefined measurement time or a maximum number of droplets. Such criteria are extremely limited and may fail to capture the physical changes in the spray characteristics induced by the operating conditions or the surrounding environment because the data rate is relatively high. Currently used statistical criteria, based on moments of the distributions of size and/or velocity, to allow the experimentalist's assessment of when to stop measuring, may also be blind to spray changes, as shown by Panão (2012).

The goal of this study is twofold. First, inspired by James et al. (2011), we introduce the *Anatomy of a Droplet-Event*. This implies the recognition of a new spray characterization layer by measuring the amount of information as an expression of the diversity generated by the non-deterministic nature of the liquid atomization process, which is reflected in the spray characteristics, such as size and velocity. Second, we propose a method for capturing the memory of a measurement contained in time-windows permeated with droplet events, which includes information on their size, velocity, and inter-arrival time (δt), relative to previous time-windows.

2. Anatomy of a Droplet-Event

In pointwise laser diagnostic techniques, such as TSTOF, each measured droplet is more than a datum to be included in the averages. It is an event: a structured observation whose information contains distinct, functional components. The droplet size D_n is a morphological component, its

velocity U_n is a kinematic component, and the inter-arrival time δt_n is an arrival component associated with the temporal texture of the measurement stream that is sensitive to particle density. Thus, each measured droplet-event can be written as

$$X_n = (D_n, U_n, \delta t_n), \quad (1)$$

where n identifies the order of the detected droplet-event. This event is not measured in isolation. It is conditioned by the measurement location $\tilde{x} = (x, y, z)$ and the operating conditions, such as the injection pressure (p_{inj}) or mass flow rate ($\dot{m}$). Therefore, the corresponding measurement context can be expressed as

$$C_n = (\tilde{x}_n, p_{inj,n}, \dot{m}_n, \dots). \quad (2)$$

The anatomy of a droplet-event $\mathcal{A}$ is intrinsically related to the non-deterministic nature of sprays, which is expressed through diversity, organization, and possible changes in the measured population. Therefore, this anatomy is introduced here not only as a decomposition of the event coordinates, but also as a map of the informational state made visible by the measurement,

$$\mathcal{A}(X_n|C_n) = \{H_I^D, H_I^U, H_I^{\delta t}, mH_{d,u}, \widehat{\mathcal{M}}_{\text{real}}, \widehat{\mathcal{M}}_{\text{corr}}, C_n\}. \quad (3)$$

The first three terms quantify the amount of information for a certain measurement alphabet (statistical classes for size, velocity, and inter-arrival time). The quantity H_I^D represents the morphological diversity of the drop sizes, indicating the number of effective drop-size states populated. The quantity H_I^U represents the kinematic diversity and indicates the number of effective drop-velocity states populated. The quantity $H_I^{\delta t}$ represents the diversity of the inter-arrival time intervals between consecutive droplet-events. In the case of δt_n , the differential informature form is especially relevant because inter-arrival times are continuous quantities whose natural scale is associated with the temporal resolution and event rate structure of the diagnostic process.

The mutual informature $mH_{d,u}$ represents the coupling between the drop size and velocity populations. This coupling is synthesized by the expression *morphokinematic organization*: which measures whether information on drop size reduces the amount of information needed to describe drop velocity, or conversely, whether velocity carries information about size. In this sense, $mH_{d,u}$ does not measure temporal memory but the organization internal to the measured droplet population.

The quantities $\widehat{\mathcal{M}}_{\text{real}}$ and $\widehat{\mathcal{M}}_{\text{corr}}$ are *memory traces* associated with measurement morphing and have different roles in the task. These are not the coordinates of a single droplet-event. Instead, they describe what is carried forward across sequences of droplet-events. Therefore, they are associated with the memory of the measurement and with the way the measured droplet population changes, or *morphs*, under a given context. These quantities are defined in Sec. 4. Finally, C_n corresponds to the measurement context, which conditions droplet-events and may change during acquisition.

What is *measurement morphing*? When the measurement context changes, such as the position, pressure, flow rate, scanning path, or even the local spray regime, the measurement does not simply record a fixed distribution of the droplet size. The occupation of classes in the measurement alphabet also changes. In this sense, the measurement *morphs*. Therefore, *measurement morphing* refers to the distribution of the measured droplet-event population as the measurement context changes. If the context is fixed, the measurement may sample an approximately stationary droplet population at a specific time. If the context changes, the measurement becomes a path through different informational states in the spray. This distinction is important for interpreting the memory of measurements. Memory is not necessarily a causal influence of one droplet over the next. Rather, from a measurement perspective, memory is what remains sufficiently organized in the droplet-event sequence to reveal what the measurement experiences and carries forward.

3. Evaluating Changes in Spray Informational State

Sprays are composed of droplets with different sizes and velocities. These droplet characteristics can be organized statistically, namely, through histograms. However, defining a histogram implies building classes as intervals that accommodate the number of droplets whose characteristics lie within each interval. To understand what a *spray informational state* is, each size or velocity class can be interpreted as a possible microstate of the measured spray. Thus, the ensemble of all possible microstates in the histogram format expresses the most probable macrostate of the spray captured by the diagnostic technique, hereafter referred to as the spray informational state.

When characterizing a spray, moments of the droplet size and velocity distributions are often used to capture the overall dynamics. However, the moments do not fully express the inherent diversity of the spray characteristics. Two drop size distributions (DSDn) may differ in scale and shape, while leading to the same first moment. Recapturing the experience of the differences observed in DSDn is possible using metrics based on information theory, as exemplified by Ferrão et al. (2025) and Panão (2025a). However, before doing so, the statistical language commonly used for spray characterization must be reframed.

A sample of N droplets of different sizes and velocities can be described once the microstates or classes are established. Each microstate/class k contains a number of droplets n_k with the corresponding characteristics. Therefore, building a histogram with the relative frequency of observed events,

$$f_k = \frac{n_k}{N}, \quad (4)$$

is equivalent to determining the weight of each microstate in the most probable macrostate captured by the diagnostic technique.

In the case of sprays, the early work of Sowa (1992) is insightful because it points to the value of

not only using the number-weighted description of sprays but also area- and volume-weighted descriptions. For instance, in spray combustion, where the Sauter Mean Diameter (SMD or D_{32}) is frequently used, the relevant distribution is related to an area-weighted DSDn. Following this idea, a general way to represent the distributions of a spray characteristic C is to consider different weights j for each microstate/class k , with $j = 0$ corresponding to number-weighted distributions, $j = 2$ to area-weighted distributions, and $j = 3$ to volume-weighted distributions. The corresponding j -weighted relative frequency is

$$w_{j,k}^C = \frac{n_k C_k^j}{\sum_{i=1}^{k_C} n_i C_i^j}, \quad (5)$$

where k_C is the total number of microstates/classes considered for spray characteristic C . For example, when $C \equiv d$ in the case of drop sizes and $j = 0$, one obtains $w_{0,k}^d = f_k = n_k/N$, because

$$\sum_{i=1}^{k_D} n_i d_i^0 = N.$$

The relative j -weighted frequency is extensive in the sense that its values depend on the number and width of the microstates/classes used to represent the characteristic spectra. Therefore, whether using regular classes or variable-size classes, and regardless of the j -weight considered, comparisons between distributions must account for class width. This is done by representing the distribution in terms of probability density, dividing the relative j -weighted frequency by the class size of the characteristic parameter C , ΔC_k , as

$$p_{j,k}^C = \frac{w_{j,k}^C}{\Delta C_k}. \quad (6)$$

From information theory, Claude Shannon (1948) found a way to quantify the amount of information associated with a non-deterministic system. In Shannon's formulation, the concepts of the amount of information and degree of transformation are intertwined. To avoid confusion with the thermodynamic concept of entropy, Panão (2025b) distinguished these concepts as *informature* and *infotropy*, respectively. Shannon's insight is useful for thermodynamics, but it is more general and implies that information is a fundamental descriptor of a physical system, as much as mass and energy.

The informature of a non-deterministic system, such as a spray, corresponds to the amount of information required to describe it. In natural units (nats), it is formulated as

$$H_{I,j}^C = - \sum_{i=1}^{k_C} w_{j,i}^C \ln(w_{j,i}^C), \quad (7)$$

where $\ln(w_{j,i}^C)$ represents the degree of surprise associated with the impact of microstate/class i on the observer when retrieving information to understand the system. Thus, the amount of information quantified by the informature can also be interpreted as the average degree of surprise.

As formulated in Eq. (7), informature is an extensive informational property of the system. Therefore, as re-interpreted by Panão (2025a), it can be converted to an intensive property in the continuous domain, although expressed in discrete format, by adding an informational grid term,

$$H_{\Delta,j}^C = \underbrace{H_{I,j}^C}_{\text{informature}} + \underbrace{\sum_{i=1}^{k_C} w_{j,i}^C \ln(\Delta C_i)}_{\text{grid term}}. \quad (8)$$

The differential informature expresses the informational state of the spray characteristics while accounting for the resolution of the measurement alphabet (i.e., statistical classes). Therefore, it is particularly relevant when the same spray characteristic is represented using non-uniform classes or when the characteristic is naturally continuous. If $\Delta C_i < 1$, the grid term can be negative, and its absolute value exceeds $H_{I,j}^C$, leading to a negative differential informature. The next section develops a method inspired by James et al. (2011), who proposed the anatomy of a bit, to assess the memory of spray measurements. The objective of this study was to provide further insight into the relevance of memory for real-time diagnostics and detection of measurement morphing.

4. What Do Memories of Spray Measurements Look Like?

The etymology of the word *memory*, from the Latin *memoria*, suggests a faculty of recording something: cognitively, the mental capacity to retain and culturally, that which preserves the past. From a measurement perspective, *memory* means “that which is kept in the measurement and carries forward.” The memory of a measurement in spray characterization is not the storage of information in a cognitive sense, but selection and retention. In the instrument–spray interaction, a measurement alphabet is established from categories such as size bins, velocity bins, and inter-arrival-time bins. The diagnostic process preserves the number of events in these categories in a statistical format, so that they can be recalled later.

After the laser diagnostic instrument performs a measurement, it converts the light signal scattered by each droplet-event into distinct characteristics. Therefore, memory is a preserved set of measurement distinctions that reflects what the flow experienced, expressed in relevant quantities under the assumptions of the instrument model. This section explains how memory is quantified from the informational relation between the usable past contained in a measurement and the future of that same measurement, using mutual information between present and future events. The reasoning is to quantify, locally in time, the amount of information about forthcoming droplet measurements contained in the immediately preceding measurements. This develops a practical notion of the memory of measurements triggered by ligament fragmentation, momentum transport, and interaction with the continuous gaseous phase, often leading to the reorganization of the population of droplets within the spray propagation path.

The laser diagnostic instrument distinguishes each event, a droplet, by its arrival time t_i , size d_i , velocity u_i , and inter-arrival time relative to the previous droplet-event, $\delta t_i = t_i - t_{i-1}$, with $\delta t_1 = 0$ for the first event. Therefore, each droplet produces a distinct symbolic event given by

$$X_i = Q(\text{bin}(d_i), \text{bin}(u_i), \text{bin}(\delta t_i)) \in \{1, 2, \dots, K\}, \quad (9)$$

where Q represents the quantization or binning operator that maps each droplet-event into an index among the $K = k_D \cdot k_U \cdot k_{\delta t}$ possible events, with k_C being the number of bins devised for each characteristic C .

In the previous section, conventional statistical classes were used to describe the occupation of the spray informational state. In contrast, assessing the memory of a measurement requires a reduced measurement alphabet size. If the number of letters/classes is too high, too many unique pairs between past and future events are formed, making the sequence appear independently distributed because there is insufficient repetition to distinguish the pattern from coincidence. Therefore, the measurement alphabet must be limited to a lower number of letters or bins k_C , marking the spray dynamics through size and velocity, and the event-rate dynamics through the inter-arrival time.

Our approach was inspired by the use of quantiles as representative characteristic parameters of a spray. The *local physical memory* corresponds to the temporal dependence between past and future events within approximately stationary regimes. Let X_i be the present measurement, P the length of the past block,

$$X_k^- = X_{k-P+1:k}, \quad (10)$$

and F the length of the future block,

$$X_k^+ = X_{k+1:k+F}, \quad (11)$$

with $(P, F) \in \{1, 2, \dots\}$. The informational relation between past and future, following the perspective of James et al. (2011), is the mutual information or informature (mH) between blocks,

$$mH(X_k^-; X_k^+). \quad (12)$$

Because the goal is to apply this approach to a real-time assessment of the memory of a measurement, small blocks produce more robust results. Therefore, considering $P = n_p$ and $F = n_f$, the mutual information becomes

$$mH(X_{k-n_p+1:k}; X_{k+1:k+n_f}) = \sum_{\mathbf{a} \in \mathcal{A}^{n_p}} \sum_{\mathbf{b} \in \mathcal{A}^{n_f}} w_{j,\mathbf{ab}} \ln \left(\frac{w_{j,\mathbf{ab}}}{w_{j,\mathbf{a}} w_{j,\mathbf{b}}} \right), \quad (13)$$

where $X_{i:j} = (X_i, \dots, X_j)$ is an ensemble of sequential events, and $mH(X_{k-n_p+1:k}; X_{k+1:k+n_f}) > 0$ measures, in nats, the amount of information about the next ensemble of droplet-events captured

by the diagnostic system that is conveyed by the present ensemble of droplet-events, and

$$\mathbf{a} = (a_1, \dots, a_{n_p}) = (X_{k-n_p+1}, \dots, X_k), \quad \mathbf{a} \in \mathcal{A}^{n_p} \quad (14)$$

$$\mathbf{b} = (b_1, \dots, b_{n_f}) = (X_{k+1}, \dots, X_{k+n_f}), \quad \mathbf{b} \in \mathcal{B}^{n_f} \quad (15)$$

$$w_{j,\mathbf{ab}} = P_j(\mathbf{A}_k = \mathbf{a}, \mathbf{B}_k = \mathbf{b}) \quad (16)$$

$$w_{j,\mathbf{a}} = \sum_{\mathbf{b} \in \mathcal{B}^{n_f}} w_{j,\mathbf{ab}}, \quad w_{j,\mathbf{b}} = \sum_{\mathbf{a} \in \mathcal{A}^{n_p}} w_{j,\mathbf{ab}} \quad (17)$$

where $w_{j,\mathbf{ab}}$ is the joint probability associated with one or multiple events, $w_{j,\mathbf{a}}$, $w_{j,\mathbf{b}}$ are the marginal probabilities, and $\mathcal{K} = \{1, \dots, K\}$ represents the symbolic alphabet.

If the spray changes, the measurement experiences a transformation that can leave a mark on its contextual memory. Otherwise, without new experiences or a change in the occupation of the measurement alphabet, no new memory is formed, and the mutual informature approaches zero. Therefore, evaluating changes implies using a time window t_w sliding through the measurement timeline. For the sake of simplicity, consider that $P = 1$ and $F = 1$. If the time window contains $\mathcal{W}$ consecutive events, the ensemble is

$$\mathcal{W}_o = \{X_o, X_{o+1}, \dots, X_{o+W-1}\}. \quad (18)$$

From this ensemble, $\mathcal{W} - 1$ subsequent pairs can be formed,

$$(X_o, X_{o+1}), (X_{o+1}, X_{o+2}), \dots, (X_{o+W-2}, X_{o+W-1}). \quad (19)$$

The joint relative frequency of subsequent events within t_w is then given by

$$\hat{f}_{pq}^{(o)} = \frac{1}{W-1} \sum_{i=0}^{o+W-2} \mathbf{1}\{X_i = p, X_{i+1} = q\}, \quad (20)$$

where $\mathbf{1}\{A\}$ is an indicator function returning 1 if A is true and 0 otherwise. For example, if the event sequence in the time window is $[1, 2, 2, 1]$, then $W = 4$, from which $W - 1 = 3$ pairs emerge,

$$(1 \rightarrow 2), \quad (2 \rightarrow 2), \quad (2 \rightarrow 1). \quad (21)$$

Thus, the relative frequency of the pair $(2 \rightarrow 2)$ is

$$\hat{f}_{2,2} = \frac{1}{3} \sum_{i=1}^3 \mathbf{1}\{X_i = 2, X_{i+1} = 2\} = \frac{1}{3}(0 + 1 + 0) = \frac{1}{3}. \quad (22)$$

The marginal relative frequencies correspond to

$$\hat{f}_p^{(o)} = \sum_q \hat{f}_{pq}^{(o)}, \quad \hat{f}_q^{(o)} = \sum_p \hat{f}_{pq}^{(o)}. \quad (23)$$

Thus, the time-resolved memory trace is

$$\widehat{\mathcal{M}}_{P,F}^{(o)} = \sum_{p=1}^K \sum_{q=1}^K \hat{f}_{pq}^{(o)} \ln \left(\frac{\hat{f}_{pq}^{(o)}}{\hat{f}_p^{(o)} \cdot \hat{f}_q^{(o)}} \right). \quad (24)$$

In this work, this quantity is denoted as the real memory trace,

$$\widehat{\mathcal{M}}_{\text{real}} \equiv \widehat{\mathcal{M}}_{P,F}^{(o)}. \quad (25)$$

This represents the raw informature carried forward by the ordered droplet-event sequence inside the time window. However, the memory trace may mix the amount by which the past reduces uncertainty about the future with apparent memory traces resulting from finite sampling and random event ordering. To resolve this issue, independence between past and future events is forced by randomly permuting future events n_{perm} times and averaging the corresponding permuted-memory traces. This yields the expected memory trace obtained from the same events but without their original temporal order. To exemplify the calculation, consider the following sequence of two possible quantized droplet events,

$$X = [1, 1, 1, 2, 2, 2], \quad (26)$$

with $\mathcal{W} = 6$. For $P = F = 1$, the past block is a single event, and the future block is the immediately subsequent event. Therefore, the window contains $\mathcal{W} - 1 = 5$ admissible past–future pairs:

$$(1 \rightarrow 1), \quad (1 \rightarrow 1), \quad (1 \rightarrow 2), \quad (2 \rightarrow 2), \quad (2 \rightarrow 2). \quad (27)$$

Equivalently, the paired past and future vectors are

$$X^- = [1, 1, 1, 2, 2], \quad X^+ = [1, 1, 2, 2, 2]. \quad (28)$$

The important point is that the mutual information calculation is not applied to the original sequence directly, but to the aligned pair list (X^-, X^+) . The empirical joint frequencies are

Pair	Count	$\mathbf{f}_{pq}$
$1 \rightarrow 1$	2	$2/5 = 0.4$
$1 \rightarrow 2$	1	$1/5 = 0.2$
$2 \rightarrow 1$	0	0
$2 \rightarrow 2$	2	$2/5 = 0.4$

Table 1. Joint relative frequencies for the real past–future pairing.

The marginal relative frequencies of the past and future vectors are

$$\underbrace{\hat{f}^-(1) = \frac{3}{5}, \quad \hat{f}^-(2) = \frac{2}{5}}_{\text{for } \hat{f}(i), i \text{ is the past event}}, \quad \underbrace{\hat{f}^+(1) = \frac{2}{5}, \quad \hat{f}^+(2) = \frac{3}{5}}_{\text{for } \hat{f}(i), i \text{ is the future event}}. \quad (29)$$

Using Eq. (24), the real memory trace is

$$\widehat{\mathcal{M}}_{\text{real}} = \sum_{p,q} \hat{f}_{pq} \ln \left(\frac{\hat{f}_{pq}}{\hat{f}_p^- \hat{f}_q^+} \right) \simeq 0.2911 \text{ nats.} \quad (30)$$

This means that, in the real ordering of the window, the present droplet-event class carries approximately 0.29 nats of information regarding the subsequent event class.

The permutation baseline must be constructed differently from the full permutation of the original sequence. The algorithm keeps the past vector X^- fixed and randomly shuffles only future vector X^+ . Thus, the past vector remains

$$X^- = [1, 1, 1, 2, 2], \quad (31)$$

whereas two possible shuffled future vectors are, for example,

$$\pi_A(X^+) = [1, 2, 2, 1, 2], \quad (32)$$

$$\pi_B(X^+) = [2, 2, 2, 1, 1]. \quad (33)$$

These shuffled vectors preserve the same future-symbol occupation as the real future vector, namely two occurrences of event 1 and three occurrences of event 2, but destroy the actual temporal alignment between past and future events. For permutation A , the surrogate pairs are

$$(1 \rightarrow 1), \quad (1 \rightarrow 2), \quad (1 \rightarrow 2), \quad (2 \rightarrow 1), \quad (2 \rightarrow 2), \quad (34)$$

which gives $\widehat{\mathcal{M}}_{\text{perm}}^A \simeq 0.01384$ nats. For permutation B , the surrogate pairs are

$$(1 \rightarrow 2), \quad (1 \rightarrow 2), \quad (1 \rightarrow 2), \quad (2 \rightarrow 1), \quad (2 \rightarrow 1), \quad (35)$$

which gives $\widehat{\mathcal{M}}_{\text{perm}}^B \simeq 0.6730$ nats. Using only these two permutations for illustration,

$$\langle \widehat{\mathcal{M}}_{\text{perm}} \rangle = \frac{\widehat{\mathcal{M}}_{\text{perm}}^A + \widehat{\mathcal{M}}_{\text{perm}}^B}{2} \simeq 0.3434 \text{ nats.} \quad (36)$$

The corrected memory trace is then

$$\widehat{\mathcal{M}}_{\text{corr}} = \widehat{\mathcal{M}}_{\text{real}} - \langle \widehat{\mathcal{M}}_{\text{perm}} \rangle. \quad (37)$$

For this particular two-permutation illustration,

$$\widehat{\mathcal{M}}_{\text{corr}} \simeq 0.2911 - 0.3434 = -0.0523 \text{ nats.} \quad (38)$$

This negative value should not be interpreted as a negative memory. This simply shows that, in such a small illustrative window and with only two permutations, a random reassignment of the

same future events can produce an apparent past–future mutual information larger than that of the real ordering. In the actual algorithm, many permutations are used so that $\langle \widehat{\mathcal{M}}_{\text{perm}} \rangle$ estimates the finite-sampling baseline associated with the same past-event occupation, future-event occupation, and number of past–future pairs. Therefore, $\widehat{\mathcal{M}}_{\text{corr}}$ estimates the excess temporal association of the real measurement order beyond the apparent association expected from the finite sampling and marginal symbol occupation.

This distinction is central to the interpretation of the measurement morphing. The real memory trace, $\widehat{\mathcal{M}}_{\text{real}}$, quantifies the raw carried-forward informature of the ordered measurement sequence. The corrected memory trace, $\widehat{\mathcal{M}}_{\text{corr}}$, estimates whether this carried-forward informature exceeds what is expected from the same events under a random sequencing. Thus, when the measurement context is fixed and $\widehat{\mathcal{M}}_{\text{corr}} \approx 0$, the droplet-event stream may be interpreted as approximately exchangeable, although it is still morphokinematically organized through $mH_{d,u}$. When the context changes, either because the spray itself evolves or because the measurement location changes, $\widehat{\mathcal{M}}_{\text{real}}$ may react because the droplet-event sequence becomes a path through which spray informational states change. In this sense, the memory of a spray measurement is the informational trace of measurement morphing: what is retained in the measurement and carried forward as the measured spray state changes.

The next section describes the experimental setup, laser diagnostic technique, and further details on the measurement methods used. Subsequently, we explored the infodynamics approach to spray diagnostics in two sections: *i*) from the perspective of locally characterizing the spray informational state, and *ii*) from the perspective of the method used to probe the possibility of capturing the memory of measurements when the spray changes.

5. Experimental Setup and Measurement Methods

The experimental setup used in this study consists of a TSTOF measurement device (see Figure 1) for droplet characterization and a closed-loop spray chamber, in which only the pump rate can be adjusted. Two sensors with current-loop interfaces were installed to monitor the pressure and flow rate during the spray process. The spray was generated using a flat-fan nozzle from Lechler.

Two parameters were varied during the experiments: the injection pressure (0.68–1.2 bar) and the measurement position x from 5 mm to 50 mm within the spray ($y = 0$ mm) at a distance of 300 mm from the injector nozzle. These parameters were recorded using additional sensors for the pressure, flow rate, and position.

Two types of measurements were conducted: static and dynamic measurements. In the 81 static measurements, all parameters were kept constant, such that each detected droplet could be uniquely assigned to a single pressure, flow rate, and measurement position. In the three dynamic mea-

surements, the injection pressure and measurement location parameters were varied in different combinations. A photograph of the experimental setup, including the closed-loop spray chamber and measurement probe, is shown in Figure 1.

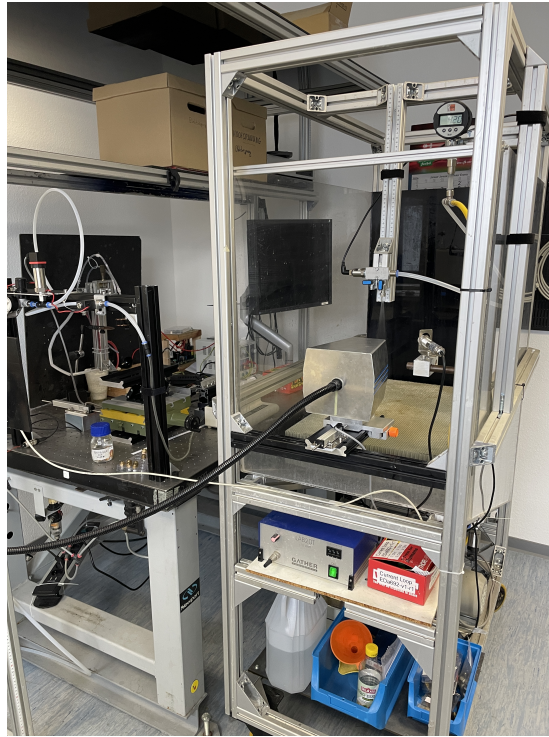


Figure 1. Photograph of the experimental setup showing the closed-loop spray chamber and SpraySpy[®] measurement probe.

The basic principle of TSTOF technology, which combines time-shift and time-of-flight methods, is based on measuring the interaction of a moving particle with shaped light beams. These beams are typically focused laser beams with a Gaussian intensity profile and do not impose specific requirements on the coherence properties of the light source. To generate a time-varying scattered-light signal, the particle must pass through the light beam at a certain velocity. The scattered light was detected as a time-dependent signal. In principle, the light beams can also be moved relative to the static particles. TSTOF is a counting measurement technique that detects the time-dependent light scattering of individual particles and determines their properties from this information. In terms of measurable droplet size and velocity, the TSTOF is comparable to Phase Doppler Interferometry (PDI). The TSTOF method was first introduced by Semidetnov (1985) and Pavlovskii & Semidetnov (1991) and was further developed at TU-Darmstadt Albrecht et al. (2013). A detailed and up-to-date description of the TSTOF measurement principle can be found in Schaefer et al. (2026).

Single-point laser diagnostics provide a time-ordered sequence of validated droplet event data.

Each event is written as

$$e_i = (t_i, d_i, u_i, \delta t_i), \quad (39)$$

where t_i is the arrival time of the i -th detected droplet, d_i is its diameter, u_i its velocity, and $\delta t_i = t_i - t_{i-1}$ the inter-arrival time. Conventional spray characterization usually proceeds by estimating local statistics of droplet size, velocity, flux, and derived quantities such as arithmetic or Sauter mean diameters, respectively. The present method adds a complementary question: does the *order* in which validated droplets are measured contain additional information?

5.1. Measurement alphabet

The continuous droplet event is first mapped into a discrete measurement alphabet. Diameter, velocity, and inter-arrival time are binned as

$$b_d(i) \in \{1, \dots, k_d\}, \quad b_u(i) \in \{1, \dots, k_u\}, \quad b_{\delta t}(i) \in \{1, \dots, k_{\delta t}\}. \quad (40)$$

The quantized droplet event is then represented by a single symbol,

$$X_i = Q(b_d(i), b_u(i), b_{\delta t}(i)) \in \{1, \dots, K\}, \quad (41)$$

where

$$K = k_d k_u k_{\delta t}. \quad (42)$$

Equivalently, the multidimensional bin index may be collapsed into one integer using a mixed-radix mapping,

$$X_i = 1 + (b_d(i) - 1) + (b_u(i) - 1)k_d + (b_{\delta t}(i) - 1)k_d k_u. \quad (43)$$

This operation does not introduce any new physical assumptions. Instead, it defines a reproducible alphabet for the droplet-event classes. The bin boundaries are kept fixed throughout the dataset so that a given symbol has the same physical meaning in each time window.

5.2. Sliding windows

The symbolic sequence $X_1, X_2, \dots, X_N$ is analysed in sliding physical-time windows,

$$\omega(t_i) = (t_i - \tau_\omega, t_i], \quad (44)$$

where τ_ω is the window duration, and t_i is the window-end instant. The sequence of window-end instants is defined as

$$t_i = t_0 + \tau_\omega + (i - 1)\Delta t_\omega, \quad i = 1, 2, \dots, \quad (45)$$

where Δt_ω is the sliding-window step. At each t_i , only droplet events satisfying $t_i - \tau_\omega < t \leq t_i$ are retained for the local memory calculation.

The window duration τ_ω must be sufficiently long to contain sufficient validated droplet events for estimating probabilities (see Fig. 2), but short enough to preserve the local changes in the spray state. Thus, τ_ω controls the statistical support of each estimate, whereas Δt_ω controls the temporal resolution with which the memory trace is updated.

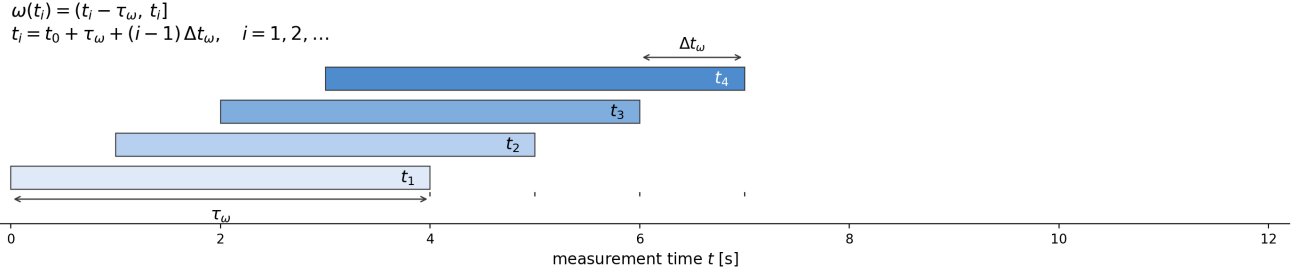


Figure 2. Sliding-window evaluation of the droplet-event sequence. At each window-end instant t_i , only the events inside $\omega(t_i) = (t_i - \tau_\omega, t_i]$ are used to estimate the local memory metrics. The window duration τ_ω controls statistical support, while the step Δt_ω controls the temporal resolution of the memory trace.

5.3. Past–future blocks

Inside each window, past and future blocks are constructed from the local symbol sequence. For a past length P and future length F ,

$$X_k^- = X_{k-P+1:k}, \quad X_k^+ = X_{k+1:k+F}. \quad (46)$$

In the setting used for the main analysis, $P = 2$ and $F = 1$, so that

$$X_k^- = (X_{k-1}, X_k), \quad X_k^+ = X_{k+1}. \quad (47)$$

Thus, the method tests whether a two-event measurement history helps predict the next droplet-event class. If the window contains N_ω symbols, the number of admissible past–future pairs is $M = N_\omega - P - F + 1$.

5.4. Real memory trace

The real memory trace in a window is defined as the mutual informature between past and future blocks,

$$\widehat{\mathcal{M}}_{\text{real}}^\omega(T_i) = mH(X^-; X^+) = \sum_p \sum_q \hat{f}_{pq}^\omega \ln \left(\frac{\hat{f}_{pq}^\omega}{\hat{f}_p^{\omega} \hat{f}_q^{\omega}} \right), \quad (48)$$

where $\hat{f}_{pq}^\omega$ is the empirical relative frequency with which past block p is followed by future block q , and $\hat{f}_p^{-,\omega}$ and $\hat{f}_q^{+,\omega}$ are the corresponding marginal relative frequencies. Natural logarithms are used, so the unit is nats.

For $P = 2$ and $F = 1$, this quantity measures how much the two most recent droplet-event classes reduce the uncertainty regarding the next droplet-event class. A large value indicates that different two-event histories are followed by different future-event distributions. A small value indicates that the local event order adds little predictive information beyond the symbol distribution itself.

5.5. Permutation baseline and corrected memory

Finite samples can produce positive mutual information even when the true event order is random. To estimate this apparent contribution, the future blocks are randomly shuffled, while the past blocks were kept fixed as follows:

$$\left\langle \widehat{\mathcal{M}}_{\text{perm}}^\omega(\tau_i) \right\rangle = \frac{1}{n_{\text{perm}}} \sum_{r=1}^{n_{\text{perm}}} mH(X^-; \Pi_r(X^+)), \quad (49)$$

where $\Pi_r(X^+)$ is the r -th random permutation of the future-block vector. This operation preserves the number of samples and the marginal occupation of past and future states but destroys their actual temporal alignment. The corrected memory trace is then

$$\widehat{\mathcal{M}}_{\text{corr}}^\omega(\tau_i) = \widehat{\mathcal{M}}_{\text{real}}^\omega(\tau_i) - \left\langle \widehat{\mathcal{M}}_{\text{perm}}^\omega(\tau_i) \right\rangle. \quad (50)$$

Therefore, $\widehat{\mathcal{M}}_{\text{corr}}^\omega$ estimates the part of the past–future dependence that exceeds the finite-sampling baseline. Values near zero indicate that the measured ordering does not provide resolved predictive information beyond the random re-pairing of the same symbols. Negative values do not imply negative memory; they indicate that the real mutual information is below the permutation baseline in that time window. Persistent positive excursions are the clearest evidence of a resolved measurement memory.

5.6. Informational macrostate and marginal-change diagnostics

Beyond the past–future dependence captured by $\widehat{\mathcal{M}}_{\text{real}}$ and $\widehat{\mathcal{M}}_{\text{corr}}$, two complementary parameters are computed in each sliding window $\omega(t_i) = (t_i - \tau_\omega, t_i]$ to track how the local informational macrostate of the spray is occupied and how it transforms from one window to the next.

Informational macrostate, $H_{I,0}^\omega$. The histogram of droplet-event symbols inside $\omega(t_i)$ represents the most probable informational macrostate of the local spray at the alphabet resolution defined in

Sec. 5.1. Using the same number-weighted convention adopted for the event-level statistics, let

$$\hat{f}_k^\omega(t_i) = \frac{1}{N_\omega} \sum_{n: t_n \in \omega(t_i)} \mathbf{1}\{X_n = \xi\}, \quad \xi = 1, \dots, K, \quad (51)$$

be the relative frequency of symbol $\xi = \mathcal{Q}(b_d, b_u, b_{\delta t})$ inside the window representing a quantized droplet-event, with N_ω the number of droplet-events satisfying $t_n \in \omega(t_i)$ and $K = k_d k_u k_{\delta t}$ the size of the quantized measurement alphabet. This alphabet is different from those used to determine the informature of drop size, velocity, and interarrival time intervals. The corresponding windowed informature is

$$H_{I,0}^\omega(t_i) = - \sum_{k=1}^K \hat{f}_k^\omega(t_i) \ln \hat{f}_k^\omega(t_i), \quad (52)$$

expressed in nats. A low value of $H_{I,0}^\omega$ means the window uses only a few symbols, or uses them very unevenly, whereas a higher value reflects a more diverse occupation of the measurement alphabet. While $\widehat{\mathcal{M}}_{\text{corr}}$ quantifies the past-future temporal dependence between droplet-events, $H_{I,0}^\omega$ quantifies the diversity of the local alphabet. A concurrent change in $\widehat{\mathcal{M}}_{\text{corr}}$ and $H_{I,0}^\omega$ is therefore stronger evidence of a transformation in the informational macrostate of the spray than either quantity taken in isolation.

Marginal change with Jensen–Shannon divergence, D_{JS}^ω . To detect how the marginal symbol distribution evolves between successive windows, the Jensen–Shannon divergence is computed as

$$D_{\text{JS}}^\omega(t_i) = D_{\text{JS}}\left(\hat{f}^\omega(t_{i-1}), \hat{f}^\omega(t_i)\right), \quad (53)$$

with

$$D_{\text{JS}}(\hat{f}, \hat{g}) = \frac{1}{2} \sum_{k=1}^K \hat{f}_k \ln \frac{\hat{f}_k}{\bar{f}_k} + \frac{1}{2} \sum_{k=1}^K \hat{g}_k \ln \frac{\hat{g}_k}{\bar{f}_k}, \quad \bar{f}_k = \frac{\hat{f}_k + \hat{g}_k}{2}. \quad (54)$$

By definition, classes with zero counts are equal to zero, and natural logarithms are used so that D_{JS}^ω is expressed in terms of nats. D_{JS}^ω is a local marginal change detector that responds to abrupt reorganizations of the measurement alphabet between consecutive windows. Together, $H_{I,0}^\omega$, $\widehat{\mathcal{M}}_{\text{corr}}$, and D_{JS}^ω form a diagnostic triad that separates the resolved measurement memory from the finite-sampling structure and identifies the signatures of measurement morphing in spray characterization.

5.7. Diagnostics and interpretation

The corrected memory trace is interpreted together with the marginal informature of the local alphabet, with the uniqueness ratio

$$r_{Upf} = \frac{\#\{\text{unique } (X^-, X^+) \text{ pairs}\}}{M}. \quad (55)$$

This quantity diagnoses undersampling: if r_{Upf} is close to one, almost every past–future pair is unique, and the mutual information estimate is poorly supported. The ideal would be that $r_{Upf} \in]0.2; 0.6]$.

Regarding interpretation, this method extends the conventional spray statistics rather than replacing them. The usual analysis describes the local distributions of droplet size, velocity, and flux. The memory trace questions whether the order of validated droplet events is significant. If $\widehat{\mathcal{M}}_{\text{corr}}^\omega \approx 0$, the data are consistent with an i.i.d.-like local sampling interpretation at the selected alphabet, window length, and memory horizon. If $\widehat{\mathcal{M}}_{\text{corr}}^\omega > 0$, the measurement stream contains temporal organization beyond the finite-sampling structure, suggesting droplet packets, clustering, intermittency, or coherent structures crossing the probe volume. A negative corrected memory trace, $\widehat{\mathcal{M}}_{\text{corr}} < 0$, indicates that the actual chronological pairing of past and future droplet-event blocks is less predictive than the average random pairing. Thus, no resolved event-order memory is detected in that window, and the apparent dependence is dominated by finite-sampling and alphabet-occupation effects. In experimental terms, the droplet-event stream may still reflect a changing local spray population. However, its chronological order does not provide additional predictive information for the selected alphabet resolution and memory horizon.

6. Results and Discussion

The Results and Discussion section is organized into two parts. The first part is dedicated to the local spray characterization and its infodynamic structure, and the second part is dedicated to the changes in the spray captured by the memory trace in a single-point measurement. For the quantization of droplet-events, we used $k_D = k_U = k_{\delta t} = 2$, $P = 2$, and $F = 1$.

6.1. Local Spray Characterization

The local characterization of the spray considers several values of the injection pressure. Fig. 3 shows that we can decrease D_{32} by a third when almost doubling the injection pressure, while the velocity only increases by 10%, and $\overline{\delta t}$ varies in order of magnitude from the periphery to the center, where it is lower because of the higher density of the droplets. In fact, there is a correlation between $\overline{\delta t}$ and the number of acquired samples given by $\overline{\delta t} = 3.5 \times 10^5 / N$ (with $R^2 = 0.992$).

By adding infodynamic quantities as a new characterization layer, our goal is to characterize the anatomy of the droplet-event.

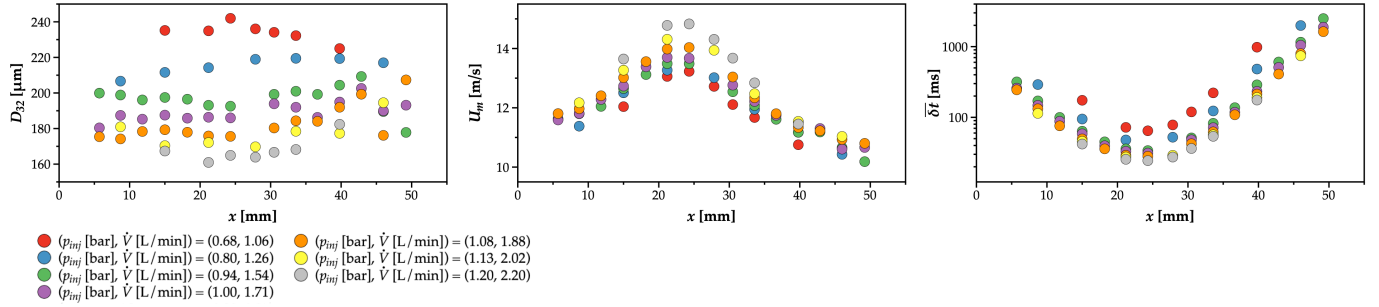


Figure 3. Local spray characteristics (Sauter mean diameter, D_{32} , mean velocity, U_m , and average inter-arrival time between consecutive droplets, $\overline{\delta t}$) for injection pressures between X bar and Y bar.

Fig. 4 shows the local profiles of several parameters considered in the anatomy of the droplet-event, expressed in Eq. (3). A higher injection pressure favored liquid breakup, generating smaller droplets (Fig. 3), but also less morphologically diverse (lower differential informature, see Fig. 4). The opposite occurs for kinematic morphology.

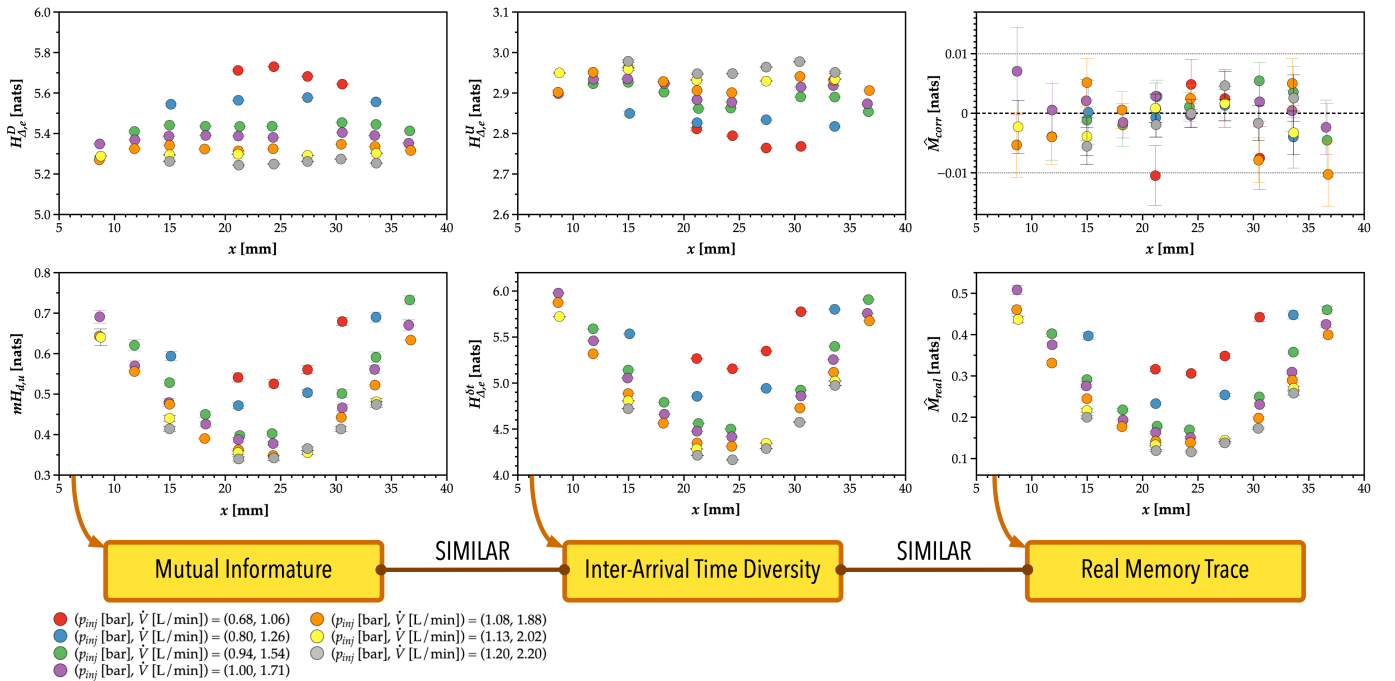


Figure 4. Local anatomy of droplet-event considering the differential ($H_{\Delta}^D, H_{\Delta}^U, H_{\Delta}^{\delta t}$) and mutual informature ($mH_{d,u}$), and both real ($\hat{M}_{real}$) and corrected ($\hat{M}_{corr}$) memory traces for injection pressures (C_{pinj}) between X bar and Y bar.

Before analyzing what is similar and what it means, a comment is due to the corrected memory trace $\hat{M}_{corr}$, which is close to zero for these local measurements. The real memory trace $\hat{M}_{real}$ can be affected by finite sample effects, and with a suitable permutation baseline applied to it,

as in Eq. (37), what remains is the actual temporal coupling between consecutive droplet-events. If $\widehat{\mathcal{M}}_{corr} \approx 0$, local measurements under stable operating conditions have no robust sequential contextual memory. This indicates that the order in which the validated droplets are measured does not add much predictive information beyond the local distribution of droplet classes, which is what we expect from local spray characterization. Finally, there is a similar local behavior between the radial profiles of the morphokinematic organization of the spray quantified by the mutual infromature ($mH_{d,u}$), inter-arrival temporal diversity between subsequent droplet-events ($H_{\Delta,e}^{\delta t}$), and real memory trace $\widehat{\mathcal{M}}_{real}$ quantifying the amount of information carried between past and future droplet-events.

The $mH_{d,u}$, $H_{\Delta,e}^{\delta t}$, and $\widehat{\mathcal{M}}_{real}$ are three distinct perspectives of the same local spray organization. The probe volume does not sample the droplet diameter, velocity, and arrival time as three completely unrelated observables. A droplet detected at a point is the result of the local morphokinetic state of the spray, that is, how droplets are produced, transported, clustered, dispersed, accelerated, or recirculated before crossing the measurement volume. Therefore, if the spray evolves spatially through regions of stronger or weaker organization, it is plausible that the diameter-velocity relation, diversity of interarrival times, and event-to-event memory trace all vary coherently.

In spray science, the intrinsic link between drop size and velocity is already known, despite their diversity. Although large droplets may retain more momentum, small droplets (discrete phase) may follow the carrier flow (continuous phase) more closely, and different atomization or transport regimes affect the populations of different regions of the $d - u$ plane. In regions with high droplet density flux, more droplets eventually lead to lower inter-arrival temporal diversity. The real memory trace is not independent of morphokinetic and sequential droplet-event organization. This similarity suggests that the temporal memory trace detected in the event sequence is linked to the same local spray organization that couples the droplet size, velocity, and arrival statistics.

A higher δt diversity suggests the intermittent presence of different patterns, which is likely related to greater momentum exchanges between the spray boundary and the surrounding environment. In regions where the arrival-time structure becomes richer, the sequence of droplet events also tends to carry more real past-future dependence, explaining the similarity between $H_{\Delta,e}^{\delta t}$ and $\widehat{\mathcal{M}}_{real}$. On the other hand, while the measurement instrument and conditions could lead to a purely random variation of the data rate and influence δt , it does not necessarily mean that the physics of droplet transport is changing. However, the similarity between $mH_{d,u}$ and $\widehat{\mathcal{M}}_{real}$ shows that the memory trace does not only detect more or fewer temporally related droplets, but appears to follow changes in the coupled morphokinematic state of the measured droplets.

From the perspective of laser diagnostics, this result indicates that the real memory trace is not merely a mathematical feature of a symbolic sequence. Its spatial evolution follows trends that are already visible in physically interpretable quantities, namely, the organization of the diameter-velocity plane and the diversity of droplet inter-arrival times. This suggests that $\widehat{\mathcal{M}}_{real}$ is sensitive

to the same local spray organization that affects the droplet morphology, kinematics, and arrival timing. Nevertheless, because $\widehat{\mathcal{M}}_{\text{corr}} \approx 0$, the chronological ordering of the events does not provide a resolved predictive memory beyond the finite-sampling baseline at the selected alphabet resolution and memory horizon. From an infodynamic standpoint, this result supports the usefulness of local spray characterization based on laser diagnostic instruments, confirming that the measurements captured not only the average morphokinematic state of the spray but also the diversity inherent to the nondeterministic nature of the atomization process. The next question is whether memory traces can capture local temporal changes while measurements are ongoing.

6.2. Spray Changes Reveal Measurement Morphing

Three cases were considered: (A) variation in the injection pressure while fixing the measurement position, (B) variation in the position using the same injection pressure, and (C) variation in the position in a spray that also changes its injection pressure (see Fig. 5).

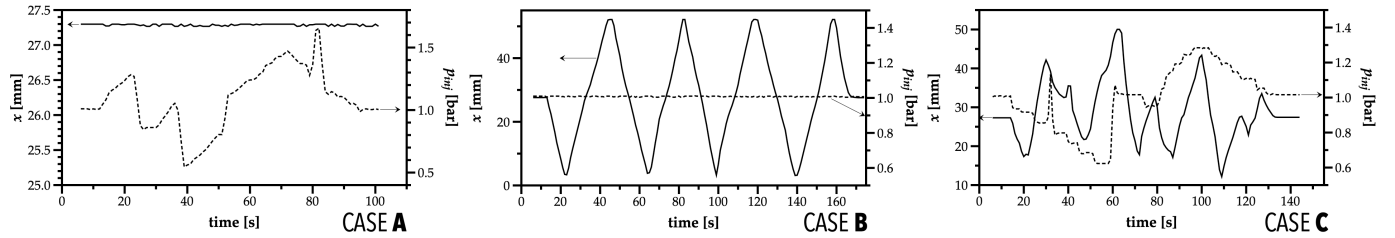


Figure 5. Injection pressure and position profiles for the three case-studies (A, B, C) used to evaluate measurement morphing reflected in its memory.

For the three cases considered, Figs. 6 to 8 show the degree of correlation between the changes in the average spray characteristics induced by variations in the injection conditions through the supply pressure and the location of the TSTOF instrument. As expected, droplet morphology was affected by variations in the injection pressure. Variations in the position do not affect the drop size and velocity, and only the inter-arrival time is sensitive to either of the two variations considered. We argue that such spray characteristics would provide overall information about the spray but would disclose changes in the relationship between the spray and its measurement. Such changes induce differences in liquid atomization or local characteristics of the spray, depending on the measurement location. The nondeterministic character of the spray can capture this change through infodynamic parameters. For example, changes in the diversity of quantized drop-events given by H_1 appear to be synchronized with variations in the injection pressure, and sudden changes appear to be synchronized with peaks in the Jensen-Shannon divergence. The memory trace also varied significantly, implying that the measurement was morphing. However, the question is whether such morphing can provide any signature of the cause of the changes. The bandwidth of $\widehat{\mathcal{M}}_{\text{corr}} \in [-0.01, 0.01]$ previously considered as the threshold of no robust contextual memory, is

overcome, which we can interpret as the emergence of resolved measurement memory, meaning that part of the past–future dependence in the measured droplet-event sequence is distinguishable from the dependence expected purely from finite-sample effects, capturing transitions in liquid atomization induced by injection pressure variations.

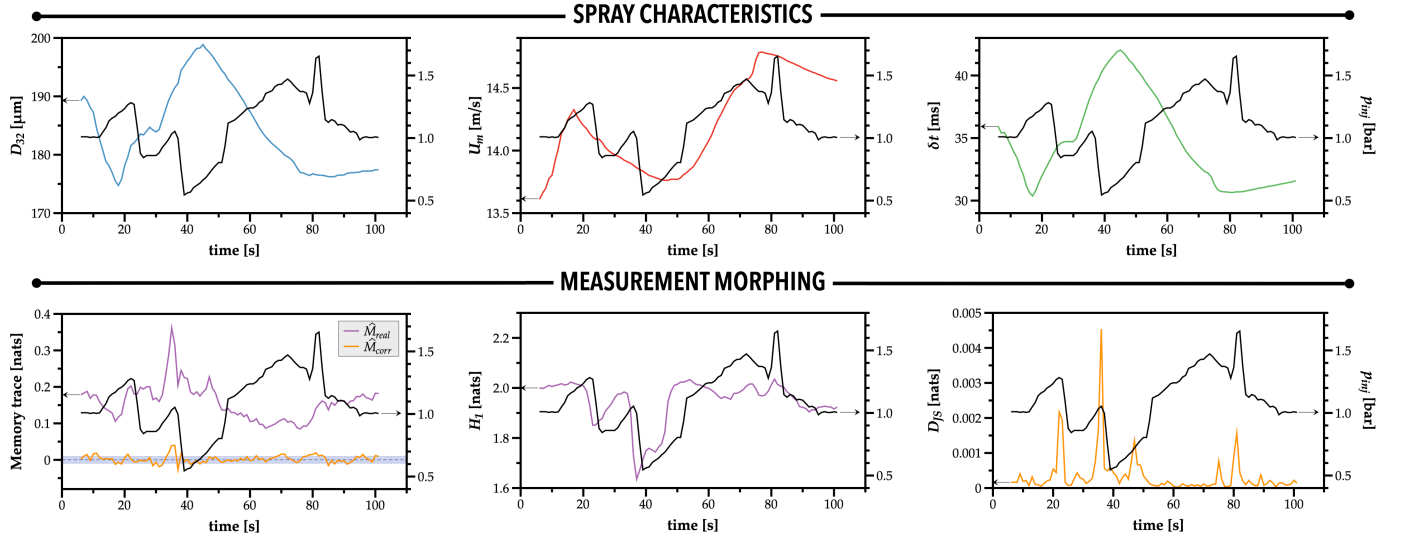


Figure 6. CASE A: Effect of varying the injection pressure at a fixed position on the spray characteristics (D_{32} , U_m , δt) and infodynamic parameters related to measurement morphing (memory trace $\widehat{M}_{real}$, $\widehat{M}_{corr}$; informational macrostate of drop-event H_1 ; marginal change with the Jensen-Shannon Divergence D_{JS}).

When the injection pressure is fixed at 1 bar and the position changes, the measurement instrument moves through the spray and captures information from different regions. However, in this radial region, only the inter-arrival time intervals appear to change, while the measurement morphs, due to the accumulated effect of different number of particles acquired, depending on the region (see Fig. 3 and the correlation mentioned before). The velocity captures some oscillations because the TSTOF instrument probes different regions with different average velocities, but these are within a 3% variability, rendering any extrapolation to the variation imposed on the position dubious. However, the results for the infodynamic parameters are shown in Fig. 7 clearly captures the measurement morphing caused by the variation in the TSTOF probe position through the real memory trace $\widehat{M}_{real}$ and the drop-event quantized diversity H_1 . However, both infodynamic parameters exhibited a plateau periodic structure coinciding with the turning point of the laser diagnostic instrument, which moved the measurement volume in the opposite direction, necessitating an explanation.

A closer look at the data showed that in these periods, the data rate decreased to levels below a certain threshold, and very few droplet-events were accounted for, implying a certain stagnation in the amount of acquired information. This means that the diversity stagnates ($H_1 \approx \text{const.}$), and the past–future dependence in those time-windows ($\widehat{M}_{real} \approx \text{const.}$), indicating no relevant changes in the temporal organization of the spray. A final note regards the peaks observed in

the macrostate-change indicator of the Jensen-Shannon divergence that evaluates any changes in the population of quantized droplet-events between time-windows. The plot in the bottom right corner shows a coincidence between the D_{JS} peak and a small spike in the real memory trace. Considering the meaning of each parameter, the peak in D_{JS} alerts for a relevant change in the distribution of quantized droplet-events, but the fact that it coincides with a $\widehat{\mathcal{M}}_{real}$ spike that indicates a greater temporal structure order in the droplet-events implies that the distribution changed with sequential structure, showing a morphing effect on the measurement.

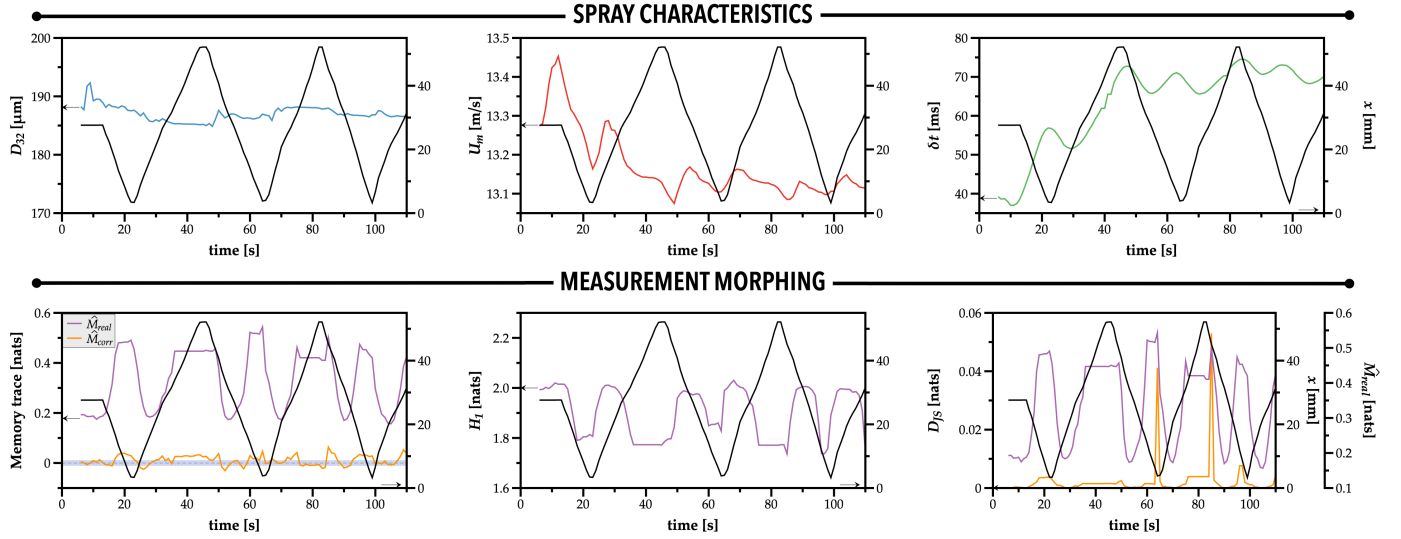


Figure 7. CASE B: Effect of varying the TSTOF measurement volume position at a fixed injection pressure on the spray characteristics (D_{32} , U_m , δt) and infodynamic parameters related to measurement morphing (memory trace $\widehat{\mathcal{M}}_{real}$, $\widehat{\mathcal{M}}_{corr}$; informational macrostate of drop-event H_1 ; marginal change with the Jensen-Shannon Divergence D_{JS}).

The third case (C) experimentally simulates contingent variations in both operating conditions with oscillations in the injection pressure and a measurement instrument that experiences a random sweep of the spray in the x -direction. Although the average velocity is relatively insensitive to these variations, the size and inter-arrival time between droplet-events are not. However, there is still no discernible pattern between the evolution of the spray characteristics and the contingent changes simulated. The plot of δt also includes the evolution of the data rate, showing a high variability caused by the induced changes, leading to substantial differences in the ability of the TSTOF instrument to acquire information on the target. Nonetheless, adding a new infodynamic characterization layer in the measurement analysis related to the spray local transient organization provides further insight into the type of information that is being carried. The manner in which $\widehat{\mathcal{M}}_{real}$ follows variations in the measurement volume position implies that the real memory trace captures the changes induced in the population and data-rate structure. In addition, the periods showing a positive resolved memory trace $\widehat{\mathcal{M}}_{corr} > 0$ indicate that probing different regions of the spray reveals how the sequence of droplet-event classes contains predictive information about the following events, which would not be obtained by the random re-pairing between past and future

droplet-events. These events could be the interfacial regions of the spray with a transition between high-to-low droplet density, repeatable structures induced by variations in the injection pressure, all leading to a structured ordered sequence of events. The spray changes induced in Case C were

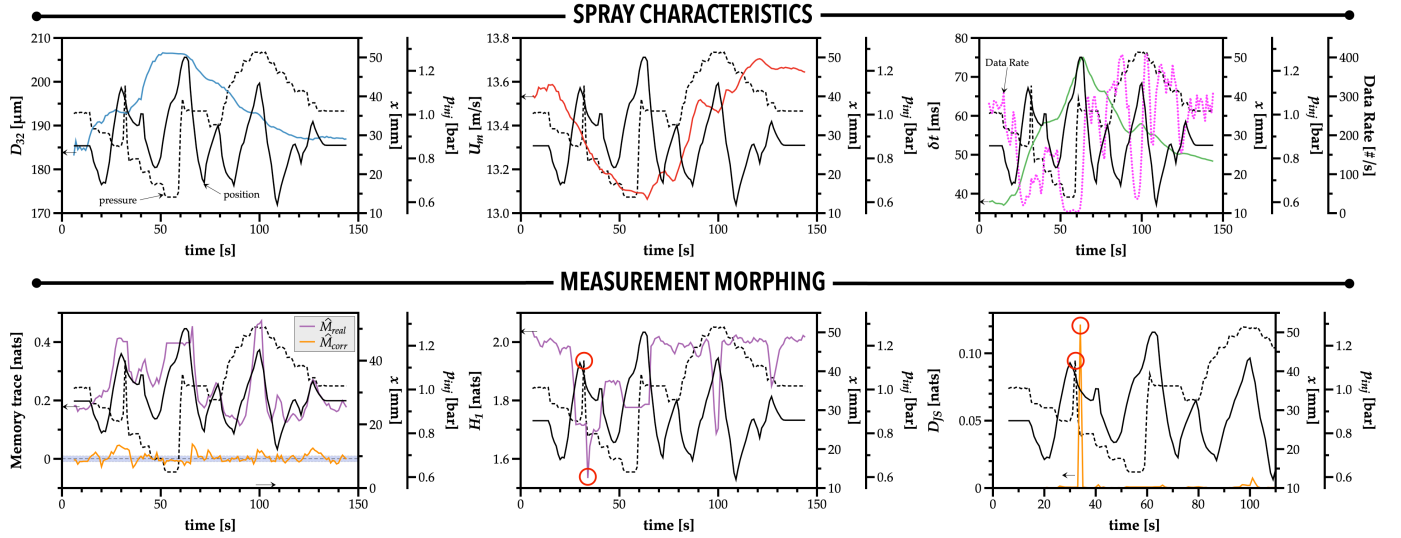


Figure 8. CASE C: Effect of varying the TSTOF measurement volume position *and* injection pressure on the spray characteristics (D_{32} , U_m , δt) and infodynamic parameters related to measurement morphing (memory trace $\hat{M}_{real}$, $\hat{M}_{corr}$; informational macrostate of drop-event H_1 ; marginal change with the Jensen-Shannon Divergence D_{JS}).

primarily through distributional and data-rate reorganization, but certain intervals also exhibited resolved event-order memory, indicating that the measured droplet events were not always similar to i.i.d. at the selected symbolic resolution. The measurement morphing behaves as an ordinary distributional sampling most of the time but occasionally carries a short-range predictive structure.

The results and discussion of cases A, B, and C clarify the distinction between spray characterization and spray monitoring. Characterization aims to describe the local droplet population under a given operating and measurement condition, usually through statistics of size, velocity, flux, and related distributions. In contrast, monitoring asks whether the measured spray remains in the same informational state or whether it is undergoing a change that may affect the validity of that characterization. This distinction is particularly relevant because sprays are intrinsically non-deterministic two-phase flow systems: even under nominally fixed Under these operating conditions, the detected droplet sequence reflected stochastic atomization, turbulent transport, clustering, intermittency, and validation effects. Therefore, infodynamics provides a useful descriptor of this non-deterministic character, not by replacing conventional statistics but by quantifying how the information carried by quantized droplet events is distributed, reorganized, and temporally structured. The proposed notion of measurement memory is useful at this interface. It adds a way of testing whether the time-ordered measurement stream behaves as repeated sampling from a stable local population or whether changes in the event alphabet, arrival structure, and past–future dependence indicate that the measured spray state is morphing. In this sense, infodynamic de-

scriptors help distinguish between two complementary situations: one in which the measurement can be treated mainly as a characterization of a local spray condition, and another in which the measurement itself becomes a monitor of the evolving spray organization. Therefore, the memory of the measurement provides a bridge between both uses of laser diagnostics, allowing one to exploit the same droplet-event data either to characterize a spray state or to detect when that state is no longer informationally the same.

7. Concluding Remarks

This study developed an infodynamic interpretation of spray measurements based on the idea that a validated droplet should be treated not only as a datum for statistical averaging but also as a droplet-event. Each droplet-event carries morphological information through its size, kinematic information through its velocity, and arrival information through its inter-arrival time. This event-based view does not replace conventional spray characterization but extends it by asking how the measured droplet population is distributed, organized, reorganized, and temporally structured during acquisition.

The first contribution of this study was the formulation of the anatomy of a droplet-event. The differential informature of droplet size, velocity, and inter-arrival time was used to describe the diversity of the local spray informational state, whereas the mutual informature $mH_{d,u}$ quantified the morphokinematic organization between droplet size and velocity. These quantities provide a new additional characterization layer for non-deterministic sprays, where mean values and distribution moments may not fully describe the diversity and organization of the measured populations. In this sense, infodynamics offers a language for describing the informational content of spray measurements without abandoning the physical meaning of the quantities already familiar with spray diagnostics.

The second contribution was the conceptual introduction of a measurement memory to probe the temporal organization of the droplet-event sequences. The real memory trace $\widehat{\mathcal{M}}_{real}$ quantifies the raw carried-forward informature between past and future droplet-event blocks inside a sliding time window. Because this quantity can be influenced by finite-sampling effects, uneven occupation of the measurement alphabet, and changes in the data rate, the corrected memory trace $\widehat{\mathcal{M}}_{corr}$ was introduced to estimate the part of the past-future dependence that exceeds the permutation baseline. Thus, $\widehat{\mathcal{M}}_{real}$ and $\widehat{\mathcal{M}}_{corr}$ have different interpretations: the former describes the temporal organization in the measured sequence, whereas the latter identifies intervals where the chronological ordering of the droplet-events carries resolved predictive information beyond the random future-block re-pairing process.

For local measurements under stable operating and measurement conditions, the corrected memory trace remained close to the finite-sampling baseline. This result is important because it sup-

ports the usual interpretation of single-point spray measurements as approximately local sampling processes at the selected alphabet resolution and memory horizons. However, the real memory trace showed spatial trends similar to those of morphokinematic organization and inter-arrival-time informature. This indicates that the raw past–future dependence is sensitive to the same local spray organization that couples droplet size, velocity, and arrival timing, even when this organization is not resolved as an additional predictive memory after correction.

Dynamic measurements revealed the central phenomenon addressed in this study: measurement morphing. When the injection pressure and/or measurement position changed during acquisition, the measurement no longer sampled a single stationary local droplet population. Instead, it followed a path through different spray informational states. The marginal informature H_1 describes the diversity of the quantized droplet-event alphabet in each window, whereas the Jensen-Shannon divergence D_{JS} detects sudden changes in the occupation of that alphabet from one window to the next. Together with $\widehat{\mathcal{M}}_{real}$ and $\widehat{\mathcal{M}}_{corr}$, these quantities show that the measurement can morph through changes in event density, droplet-event diversity, marginal alphabet occupation, and event-order organization in some intervals. Therefore, the results clarify the distinction between spray characterization and spray monitoring from an infodynamic viewpoint. Characterization aims to describe the local droplet population under the prescribed operating and measurement conditions. In contrast, monitoring asks whether the measured spray remains informationally the same or whether it undergoes a transformation that may affect the validity of that characterization. The proposed memory-of-measurement framework operates at this boundary level. When $\widehat{\mathcal{M}}_{corr}$ remains close to zero and the informational macrostate is stable, the measurement can be interpreted as a repeated characterization of the local-spray state. When H_1 , D_{JS} , $\widehat{\mathcal{M}}_{real}$, and $\widehat{\mathcal{M}}_{corr}$ vary in a coordinated manner, the same measurement can be used to monitor the evolving spray organization.

Although the present experiments were performed using the Time-Shifting Time-Of-Flight (TSTOF) technique, the proposed framework is not limited to this instrument. The essential requirement is a time-ordered sequence of validated droplet-events containing size, velocity, and arrival information. Therefore, the same reasoning may be extended to other single-point laser diagnostic techniques, including phase-Doppler interferometry, whenever the acquisition provides event-resolved droplet data for a specific application. Therefore, the broader contribution of the present work is not technique-specific but methodological: it shows how droplet-event data can be used to distinguish between a stable characterization of a local spray state and a measurement that is morphing because the spray, measurement position, or operating conditions are changing. In this sense, infodynamics provides a descriptor of the non-deterministic nature of sprays. It does not claim that every measured sequence contains resolved memory, nor does it replace classical quantities, such as the mean diameter, mean velocity, and data rate. Instead, it organizes these measurements within a broader informational view, in which the spray is characterized by the occupation, diversity, coupling, redistribution, and temporal organization of droplet-events. The

main practical implication is that convergence in conventional statistics does not necessarily imply informational stationarity, while a stable corrected memory trace supports the interpretation of the measurement as a local distributional sampling.

The proposed framework opens a route for using laser diagnostics not only to describe sprays but also to monitor when their measured informational state changes. Future work should examine the sensitivity of the descriptors to the choice of measurement alphabet, window duration, past and future block lengths, permutation baseline, and uniqueness ratio r_{Upf} . Additional injector types, operating conditions, and controlled transient measurements are necessary to determine when the resolved measurement memory becomes a persistent signature of spray dynamics and when it remains a localized feature of measurement morphing.

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Nomenclature

a	Past-block symbolic state
b	Future-block symbolic state
b_d	Diameter-bin index
b_u	Velocity-bin index
$b_{\delta t}$	Inter-arrival-time-bin index
C	Generic characteristic parameter
C_n	Measurement context of the n -th droplet-event
d	Droplet diameter [μm]
D	Droplet diameter [μm]
D_{32}	Sauter mean diameter [μm]
D_{JS}^ω	Jensen–Shannon divergence in window ω [nats]
e_i	i -th measured droplet-event
f	Relative frequency
$\hat{f}$	Empirical relative frequency
$\hat{f}_k^\omega$	Relative frequency of symbol k in window ω
$\hat{f}_{pq}^\omega$	Joint frequency of past block p and future block q
$\hat{f}_p^{-,\omega}$	Marginal frequency of past block p

$\hat{f}_q^{+, \omega}$	Marginal frequency of future block q
F	Length of the future block
$H_{I,j}^C$	Informature of the j -weighted distribution of C [nats]
$H_{\Delta,j}^C$	Differential informature of the j -weighted distribution of C [nats]
H_I^D	Informature of droplet-size diversity [nats]
H_I^U	Informature of droplet-velocity diversity [nats]
$H_I^{\delta t}$	Informature of inter-arrival-time diversity [nats]
$H_{I,0}^\omega$	Informature of the event alphabet in window ω [nats]
H_1	Marginal informature of the local event alphabet [nats]
j	Weighting index
k	Class or bin index
k_C	Number of bins for characteristic C
k_d	Number of diameter bins
k_u	Number of velocity bins
$k_{\delta t}$	Number of inter-arrival-time bins
K	Total number of quantized droplet-events
mH	Mutual informature [nats]
$mH_{d,u}$	Diameter–velocity mutual informature [nats]
M	Number of admissible past–future pairs
$\widehat{\mathcal{M}}$	Memory trace [nats]
$\dot{m}$	Mass flow rate
n	Number of droplets in a class
n_i	Number of droplets in class i
n_{perm}	Number of random permutations
n_p	Past-block length in the mutual-informature expression
n_f	Future-block length in the mutual-informature expression
N	Total number of detected droplet-events
N_ω	Number of droplet-events in window ω
p	Probability density; past-block index in p, q notation
$p_{j,k}^C$	Probability density of class k for characteristic C
p_{inj}	Injection pressure [bar]
P	Length of the past block
q	Future-block index
$\mathcal{Q}$	Quantization operator
r_{Up}	Fraction of unique past words
r_{Uf}	Fraction of unique future words
r_{Upf}	Fraction of unique past–future pairs
t	Time instant [s]

t_i	Arrival time or window-end instant [s]
t_0	Initial time instant [s]
u	Droplet velocity [m/s]
U	Droplet velocity [m/s]
U_m	Mean droplet velocity [m/s]
$w_{j,k}^C$	j -weighted relative frequency of class k
$w_{j,ab}$	Joint probability of past state a and future state b
$w_{j,a}$	Marginal probability of past state a
$w_{j,b}$	Marginal probability of future state b
W	Number of consecutive events in an illustrative sequence
$\mathcal{W}$	Sequence of consecutive droplet-events
X	Quantized droplet-event symbol
X_i	Quantized symbol of the i -th droplet-event
X_k^-	Past block of quantized droplet-events
X_k^+	Future block of quantized droplet-events
$X_{i:j}$	Sequence of quantized events from i to j
x	Measurement-position coordinate [mm]
y	Transverse measurement-position coordinate [mm]
z	Distance from nozzle coordinate [mm]

Greek Symbols

$\mathcal{A}$	Anatomy map of a droplet-event
ΔC	Bin size of characteristic C
ΔC_k	Width of class k for characteristic C
Δt_ω	Sliding-window step [s]
δt	Inter-arrival time [s]
$\bar{\delta t}$	Average inter-arrival time [s]
ξ	Generic event-alphabet symbol
Π_r	r -th random permutation
τ_ω	Sliding-window duration [s]
ω	Time window
$\omega(t_i)$	Time window ending at t_i

Superscripts

$+$	Future block
$-$	Past block
C	Characteristic parameter
d, D	Diameter-related quantity
u, U	Velocity-related quantity

δt	Inter-arrival-time-related quantity
ω	Time-windowed quantity

Subscripts

$corr$	Corrected quantity
d, D	Diameter-related quantity
f	Future-related quantity
I	Informature
inj	Injection-related quantity
j	Weighting index
k	Class, bin, or event index
p	Past-related quantity; past-block index
$perm$	Permutation baseline
q	Future-block index
$real$	Real-data quantity
u, U	Velocity-related quantity

Acronyms

AMD	Arithmetic mean diameter
DSDn	Drop size distribution
DVDn	Drop velocity distribution
JSD	Jensen–Shannon divergence
PDA	Phase Doppler Anemometry
PDI	Phase Doppler Interferometry
SMD	Sauter mean diameter
TSTOF	Time-shifting time-of-flight

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