On the Memory of Measurements in Spray Diagnostics

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ABSTRACT

In spray characterization, a measurement takes time to retrieve sufficient information to reach an adequate sample size on which statistical methods are applied. What if the spray changes during the measurement? In practice, the spray droplets may change their size and dynamics, which is analogous to establishing new "memories" of their characteristics. In the context of measurement, "memory" refers to the present signal carrying traces of the recent past, including flow, particles, light–matter interaction, and instruments. This past imprint turns raw observations into a time-dependent record rather than isolated snapshots. This study investigates how to quantify memory in measurements made by the time-shifting technique applied to spray characterization using the infodynamic concept of mutual information between successive sample frames. The assessment of "how much of the past remains in the present" presents an identifiable pattern that we can attribute to long-term measurement memories or ongoing measurement memory formation. By adding a new spray characterization layer based on the informational macrostate of the local spray, we provide non-deterministic quantifiable data that are useful for the development and validation of numerical models.

1. Introduction

A measurement is not a static, isolated data point but a dynamic entity rich in information about the temporal structure of the 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* (M. R. Panão, 2025), which is the argument for investigating the possibility of memories of measurements that open new characterization layers for understanding the role of *information*, as the basic structure of reality, in the definition of 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 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 M. R. O. Panão (2012).

The goal of this study is twofold. First, we introduce a new spray characterization layer by measuring the amount of information as an expression of the diversity present through the non-deterministic nature of the macrostate of a spray property, such as size and velocity. Second, we propose a method for capturing the memory of a measurement contained in each droplet event, which includes information on the size, velocity, and inter-arrival time (δt) relative to the previous event (with $\delta t_0 = 0$ by definition for the first detected event). The next section describes the experimental setup and the laser diagnostic technique used in the preliminary results presented here, as well as the setup used in the data acquired recently for exploring several ways of changing the spray during a measurement, which is currently under processing for inclusion in the final paper. Subsequently, we explore the infodynamics approach to spray diagnostics in two sections: *i*)from the perspective of changes in the spray informational state and *ii*) from the perspective of the method used to probe the possibility of capturing memory spray measurements. Finally, we conclude this extended abstract with some remarks.

2. Experimental Setup and Laser Diagnostic Technique

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. To monitor the pressure and flow rate during the spray process, two sensors with a current-loop interface were installed. The spray was generated by a flat-fan nozzle from Lechler.

Two parameters were varied during the experiments: the pump rate and the measurement position within the spray. These parameters were recorded using additional sensors for pressure, flow rate, and position. The measurement position was varied over a range of 50 mm, and the pressure was adjusted between 2 and 6 bar. Two types of measurements were conducted: static and dynamic. In the 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 dynamic measurements, all parameters were varied in different combinations. In total, 85 measurements were performed: 81 static and 4 dynamic measurements. A photograph of the experimental setup, including the closed-loop spray chamber and the measurement probe, is shown in Figure 1.

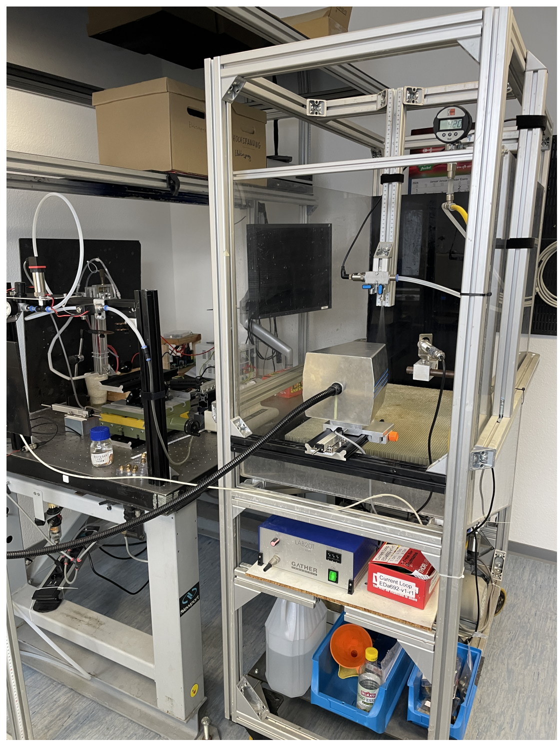

Figure 1. Photograph of the experimental setup showing the closed-loop spray chamber and SpraySpy® measurement probe.

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 is detected as a time-dependent signal. In principle, the light beams could also be moved relative to 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, TSTOF is comparable to Phase Doppler Anemometry (PDA). 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).

3. Changes in spray informational state

Sprays are composed of droplets of different sizes. The different droplet sizes in the spray can be organized using statistics, namely, through histograms. However, defining a histogram implies building classes as size intervals to accommodate a number of droplets whose size is within a certain interval. To understand what a *spray informational state* is, we must recognize each size or velocity class as a possible microstate for the spray. Thus, the ensemble of all possible microstates in the histogram format expresses the most probable macrostate of the spray, hereafter referred to as the spray informational state.

When characterizing a spray, we often use the moments of the droplet size and velocity distributions to capture the overall dynamics of the spray. However, each moment does not fully express the inherent diversity of the spray characteristics. We may have two Drop Size Distributions (DSDn) that are different in scale and shape, but the first moment results are the same. Recapturing the experience of the differences observed in DSDn is possible using metrics based on information theory, as exemplified by Ferrão et al. (2025); M. Panão (2025). However, we first need to reframe the meaning of the statistical language applied to spray characterization.

A sample of N droplets of different sizes and velocities, once the microstates/classes are established, each microstate/class k contains a certain number of droplets n_k with corresponding characteristics. Therefore, building a histogram with the relative frequency of observed events, $f_k = n_k/N$ is nothing but finding the weight of each microstate in the most probable macrostate captured by our diagnostic technique. However, in the case of sprays, the early work of Sowa (1992) is insightful because it points to the value of not using the number-weighted most common way to describe sprays, but also the area- and volume-weighted. Therefore, in spray combustion, which often uses the Sauter Mean Diameter (SMD or D_{32}), it is the mean diameter of an area-weighted DSDn. Following this, the most general way to represent drop size dsitributions is to consider the possibility of being represented by different weights j (number-weighted is $j = 0$, area-weighted is $j = 2$, and volume-weighted is $j = 3$) of each microstate/class k as

$$w_{j,k}^{C} = \frac{n_k C_k^j}{\sum_{i=1}^{k_C} n_k C_k^j} \tag{1}$$

where k_C is the total number of microstates/classes considered in the spray characteristic C (*e.g.*, $C \equiv d$ in the case of drop sizes). For example, in the number-weighted DSDn, $j = 0$, thus, $w_{0,k}^{d} = f_k = n_k/N$ because $\sum_{i=1}^{k_D} n_k d_k^0 = N$. The relative j-weighted frequency is an extensive property in the sense that values change if we alter the number of microstates/classes, maintaining the C characteristic spectrum. Therefore, whether using regular/uniform size classes, or classes of variables sizes, to compares DSDn, regardeless of the j-weigth considered, we must represent them in terms of probability density, dividing the relative j-weighted frequency by the bin size of the characteristic parameter C – ΔC_k – as

$$p_{j,k}^{C} = \frac{w_{j,k}^{C}}{\Delta C_k} \tag{2}$$

From information theory, Claude Shannon (1948) found a way to quantify the amount of information and the degree of transformation (contextualized amount of information) of a physical system containing a non-deterministic nature, two concepts mixed in Shannon's formulation that M. R. Panão (2025) distinguished as *informature* and *infotropy*, respectively, to avoid mistaking the thermodynamic concept of entropy, when applying Shannon's insight that is useful for thermodynamics, but is more general and implies considering *information* as a fundamental descriptor of a physical system, as much as mass and energy.

The informature of an indeterministic system, such as a spray, corresponds to the amount of information we need to describe it, and formulated in natural units (nats, see M. R. Panão (2025) for further details) as

$$H_{I,j} = -\sum_{i=1}^{k_C} w_{j,i} \ln(w_{j,i}) \tag{3}$$

where $\ln(w_{j,i})$ represents the degree of surprise associated with the impact of a microstate/class i on the observer when trying to retrieve information to know the system. Thus, the amount of information quantified by the informature can be interpreted as the average degree of surprise. As it is, the informature is also an extensive informational property of the system, thus, as shown by M. Panão (2025), we convert it to an intensive property in the continuous domain (although expressed in its dicrete format) by adding an informational grid term as

$$H_{\Delta,j} = H_{I,j} + \sum_{i=1}^{k_C} \Delta C_i \tag{4}$$

In this extended abstract, we considered four cases using the injection pressure to change the spray. Fig. 2 shows the changes induced in the injection pressure, except for Case 2, which was used as a reference.

The full-sample drop size and velocity distributions are shown in Fig. 3. While the Drop Size Distributions did not change significantly compared to the reference case (2), the Drop Velocity Distributions (DVDn) revealed significant changes toward higher velocity values, altering the spray dynamics. Can these changes in the informational state of the spray be captured? The differential informature of Eq. (4) is an infodynamic parameter and a cumulative measure that shows the evolution of the spray informational state. Fig. 4 shows the results for the four cases considered.

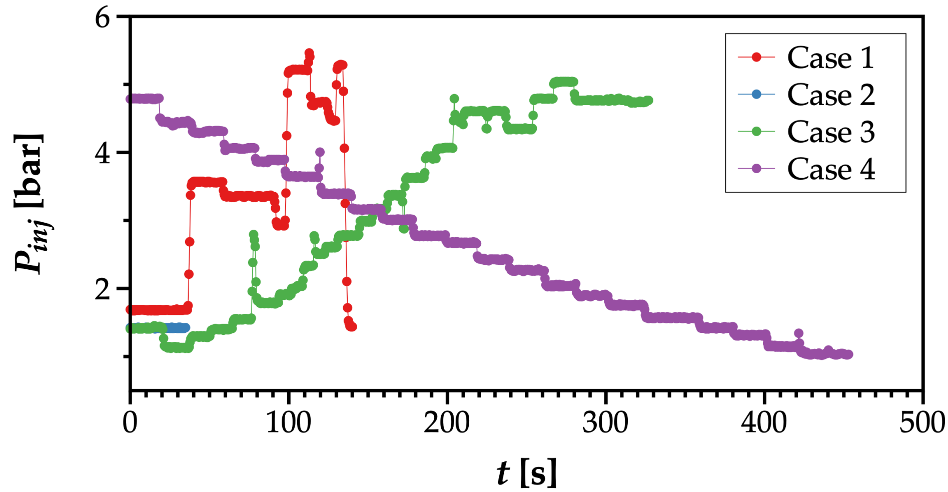

Figure 2. Injection pressure evolution in four cases to change the spray characteristics, except Case 2 to use as a reference. The total measurement time intervals in each case was: (1) 138.7 s; (2) 34.9 s; (3) 325.6 s; (4) 452.1 s.

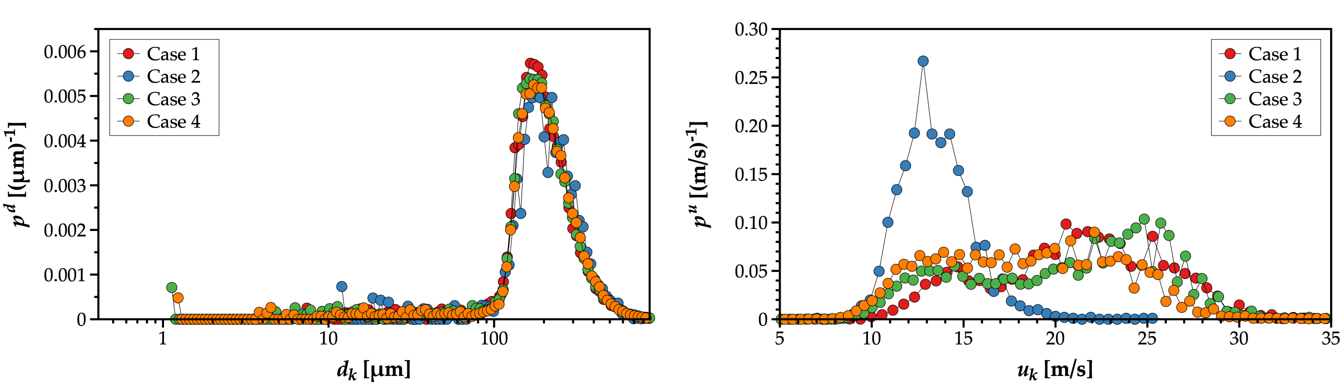

Figure 3. Drop Size (left) and Velocity (right) Distributions for the four cases considered.

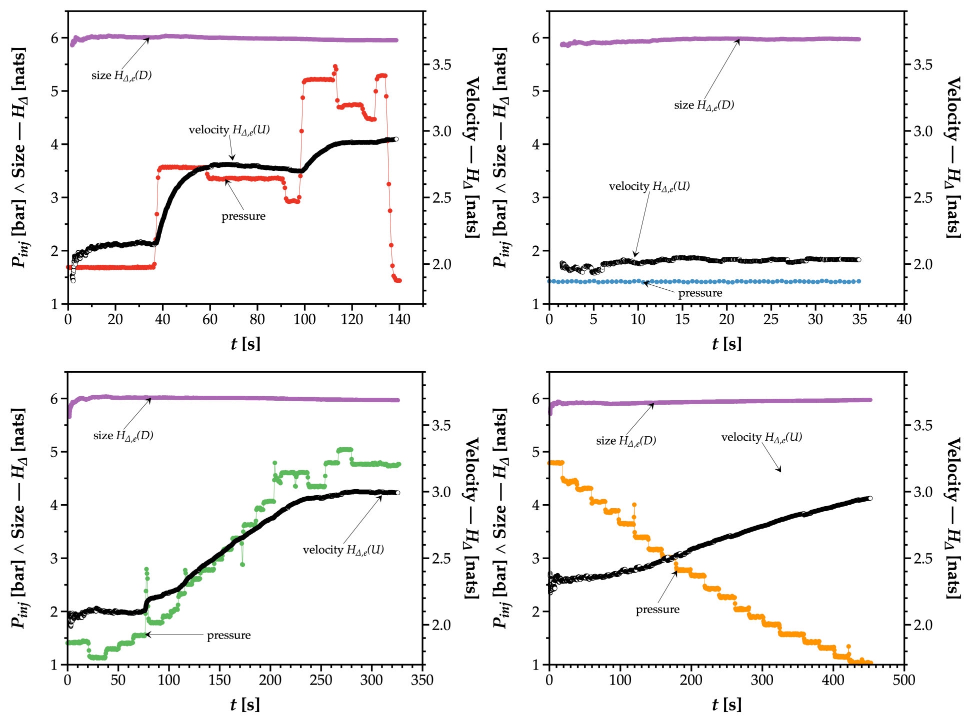

Figure 4. Evolution of the size (H^d_Δ) and velocity (H^u_Δ) differential informature for the reference case (2) and three others (1, 3, 4) where changes in the injection pressure modified the spray dynamics. While the size is not significantly affected, in the case of droplets velocity, the differential informature reacts to changes in the spray.

In the reference case (2), both measures of the differential informature remain relatively constant, as expected. However, in the other cases, the changes induced in the amount of information resulting from a change in the operating conditions are evident. This change induces the emergence of new microstates, leading to a higher diversity of droplet characteristics, as captured by the infodynamic parameter. Because the changes induced in the droplet velocity increase the diversity of values, the differential informature tends to increase. Fig. 5 shows that once the injection pressure suddenly changes before $t = 40$ $[s]$, both drop mean velocity and informature react. However, while the mean velocity behaves monotonically, the informature stabilizes and slightly decreases, indicating that the spray infodiversity saturated, but not the relative importance of more values in the new operating conditions. Although this informature is based on the same relative frequency used to compute the mean velocity, this outcome shows that informature is an independent parameter and does not compete for the same meaning as the other parameters.

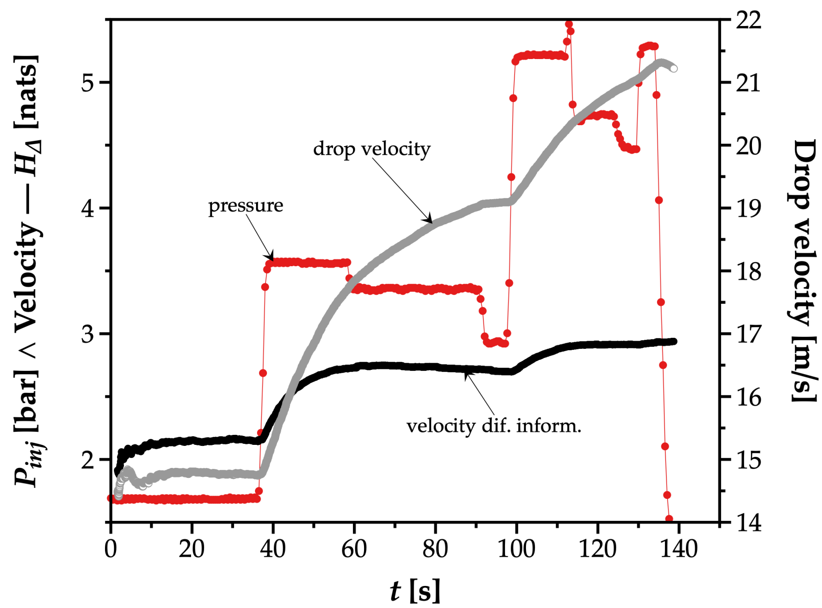

Figure 5. Evolution of droplets mean velocity ($\langle u \rangle$) and its differential informature (H^u_Δ) for case (3) where upward and downward changes in the injection pressure modified the spray dynamics. Parametrix changes are synchronized, but whereas statistical moments keep changing $d\langle u \rangle/dt > 0$, the amount of information stabilized $dH^u_\Delta/dt \approx 0$.

Nonetheless, it would take some time for the experimentalist to realize that the spray changed its operating condition because both the mean size, velocity, and informature parameters are cumulative. The next section develops a method based on James et al. (2011) for the anatomy of a bit to assess memories in spray measurements, providing further insight into their relevance in real-time diagnostics.

4. What do memories of spray measurements look like?

The etymology of the word *memory* suggests, from the Latin *memoria*, a faculty of recording something that cognitively means the mental capacity to retain, while culturally, it means 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, but selection and retention because in the instrument-spray interaction, we establish a measurement alphabet made of categories (size bins, for example), and we preserve the number of events in a statistical format to recall them later. After the laser diagnostic instrument performs a measurement, it converts the light signal scattered by each event (a droplet) into distinct characteristics. Memory is a preserved set of measurement distinctions that reflect what the flow experienced, expressed in relevant quantities under the assumptions of the instrument model. This section explains how we quantify memory based on the informational relation between the usable past contained in a measurement that affects the future using the mutual information among present and past events. The reasoning followed is to quantify, locally in time, how much information about forthcoming droplet measurements is contained in the immediately preceding measurements, developing a practical notion of temporal memory of measurements

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 event/droplet $\delta t_i = t_k - t_{k-1}$, with $\delta t_1 = 0$ for the first measured event. Therefore, each droplet produces a distinct event given by

$$X_i = \mathcal{Q}(\text{bin}(d_i), \text{bin}(u_i), \text{bin}(\delta t_i)) \in \{1, 2, ..., K\} \tag{5}$$

where $\mathcal{Q}$ represents the quantization or binning operator mapping each event into an index among the $K = k_D \cdot k_U \cdot k_{\delta t}$ possible ones, with k_C being the number of bins devised for each characteristic C. While the previous section used conventional statistics to build the alphabet that describes the spray characteristics, in the case of assessing the memory of a measurement, a high number of "letters" (classes) could result in too many unique pairs between past and present events, making the identified and independently distributed sequences without any mutual information. This implies that we need to limit the measurement alphabet to a lower number of "letters," that is, bins k_C, marking the spray dynamics (size and velocity) and event rate dynamics (inter-arrival time interval). Our approach was inspired by the use of quantiles, for example, in the definition of spray parameters, such as the Relative Span. Therefore, in the case of drop sizes, we used the 10%, 50%, and 90% to establish $k_D = 4$ classes. Regarding the drop velocity, we used $k_U = 6$ classes, but uniformly spaced. In the case of the inter-arrival time, we only used $k_{\delta t} = 2$ classes with a quantile of 50%.

The *local physical memory* corresponds to the temporal dependence between the past and future through the present within approximately stationary regimes. Therefore, let X_i be the present measurement, P be the length of the past block ($X_k^- = X_{k-P+1:k}$), and F the length of the future block ($X_k^+ = X_{k+1:k+F}$), with $(P, F) \in \{1, 2, ...\}$, the informational relation between past and future, as considered in James et al. (2011), is the mutual information between blocks $I(X_k^-; X_k^+)$. Since the goal is to apply this approach to a real-time assessment of the memory of a measurement, small blocks produce robust results, meaning we considered $P = F = 1$, thus, the mutual information results in

$$I(X_k; X_{k+1}) = \sum_{i=1}^{K} \sum_{m=1}^{K} w_{j,im} \ln \left(\frac{w_{j,im}}{w_{j,i} \cdot w_{j,m}} \right) \tag{6}$$

with $w_{j,im} = w_j \left(X_k = i, X_{k+1} = m \right)$ as the j-weighted relative frequency associated with present and future events. The mutual information $I(X_k; X_{k+1}) > 0$ measures in nats the amount of nats of information about the next droplet characteristics captured by the diagnostic system that is conveyed by the present event.

If the spray changes, it would be similar to experiencing a transformation that leaves a mark in memory. Otherwise, without new experiences, no new memories are formed, and $I(X_k; X_{k+1}) \rightarrow$

Pairs	**Counts**	$\mathbf{\hat{f}_{pq}}$
$1 \to 1$	2	$2/5 = 0.4$
$1 \to 2$	1	$1/5 = 0.2$
$2 \to 2$	2	$2/5 = 0.4$
$2 \to 1$	0	0

Table 1. Real memory trace procedure example.

0. Evaluating changes implies using a time window t_w sliding through the measurement timeline. If the time-window contains W consecutive events, this ensemble

$$\mathcal{W}_i = \{X_i, X_{i+1}, ..., X_{i+W-1}\} \tag{7}$$

we can form $W-1$ pairs of subsequent events $(X_i, X_{i+1}), (X_{i+1}, X_{i+2}), ..., (X_{i+W-2,i+W-1})$ where the joint relative frequency of subsequent events within t_w is given by

$$\hat{f}_{pq}^{(o)} = \frac{1}{W-1} \sum_{i=o}^{o+W-2} \mathbf{1}\left\{X_i = p, X_{i+1} = q\right\} \tag{8}$$

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 $[1, 2, 2, 1]$, it means $W = 4$ from which $W - 1 = 3$ pairs emerge, $(1 \to 2), (2 \to 2), (2 \to 1)$. Thus, if we want to compute $\hat{f}_{2,2}$, then

$$\hat{f}_{2,2} = \frac{1}{3}\sum_{i=1}^{3} \mathbf{1}\left\{X_i = 2, X_{i+1} = 2\right\} = \mathbf{1}\left\{1 \to 2\right\} + \mathbf{1}\left\{2 \to 2\right\} + \mathbf{1}\left\{2 \to 1\right\} = \frac{1}{3}(0+1+0) = \frac{1}{3}$$

The marginal relative frequencies correspond to $\hat{f}_p^{(o)} = \sum_q \hat{f}_{pq}^{(o)}$ and $\hat{f}_q^{(o)} = \sum_p \hat{f}_{pq}^{(o)}$. Thus, the time-resolved memory trace would be

$$\widehat{\mathcal{M}}_{P,F}^{(o)} = \sum_{p=1}^{K}\sum_{q=1}^{K} \hat{f}_{pq}^{(o)} \ln\left(\frac{\hat{f}_{pq}^{(o)}}{\hat{f}_p^{(o)} \cdot \hat{f}_q^{(o)}}\right) \tag{9}$$

However, how can we ensure that the memory trace is true if it can mix "how much past reduces the uncertainty about the future" with apparent memory traces resulting from random events in finite sampling? To resolve this issue, we force an independence between past and future events by randomly permutating future events n_{perm} times and averaging the permutated memory traces. To exemplify this consider the following sequence of 2 possible events — $[1, 1, 1, 2, 2, 2]$ — with $W = 6$, forming $W - 1 = 5$ pairs,

$$(1 \to 1), (1 \to 1), (1 \to 2), (2 \to 2), (2 \to 2)$$

In a time window with 5 of the 6 events $X_i^- = [1, 1, 1, 2, 2]$ and $X_i^+ = [1, 1, 2, 2, 2]$, the marginal relative frequencies are $\hat{f}^-(1) = 3/5, \hat{f}^-(2) = 2/5$, and $\hat{f}^+(1) = 2/5, \hat{f}^+(2) = 3/5$. Therefore, using

Eq. (9), $\widehat{\mathcal{M}}_{real} = 0.2911$ [nats], meaning the 5th event carries ≈ 0.3 [nats] of information to the 6th event. Consider in this example only $n_{perm} = 2$ permutations.

$$\begin{cases} X^A = [2, 2, 1, 1, 1, 2] \\ X^B = [1, 2, 2, 1, 1, 2] \end{cases}$$

Performing the same calculations as in the real case, $\widehat{\mathcal{M}}^A_{\pi(1)} = 0.01384$ [nats],$\widehat{\mathcal{M}}^B_{\pi(2)} = 0.17603$ [nats], thus, the average of the permutations A and B considered results in $\langle\widehat{\mathcal{M}}_{perm}\rangle \simeq 0.095$ [nats]. Therefore, the corrected memory trace corresponds to

$$\widehat{\mathcal{M}}_{corr} = \widehat{\mathcal{M}}_{real} - \langle\widehat{\mathcal{M}}_{perm}\rangle \tag{10}$$

which in the example above means that ≈ 0.1 [nats] of the real memory trace is uncertainty due to the same events but randomly sequenced. If $\widehat{\mathcal{M}}_{corr} < 0$, it does not imply that we have a negative memory trace because, by definition, the mutual information is *always* a positive quantity. Instead, it indicates that the spray is under a gradual (and not sudden) transformation, which can change the number of bins that are effectively populated in adjacent pairs and modify the magnitude of $\langle\widehat{\mathcal{M}}_{perm}\rangle$, eventually leading to a value higher than the real one. The final paper will contain more details on the memory trace approach developed here, including a {unique pairs (past, future)} verification index that should be < 0.6 unless the time window is populated with too many unique pairs, considering that without repetition, we have no data to distinguish pattern from coincidence. The following results show the memory traces obtained for the four cases considered in this extended abstract. We set the time window to 10 [s], and 0.5 [s] time steps.

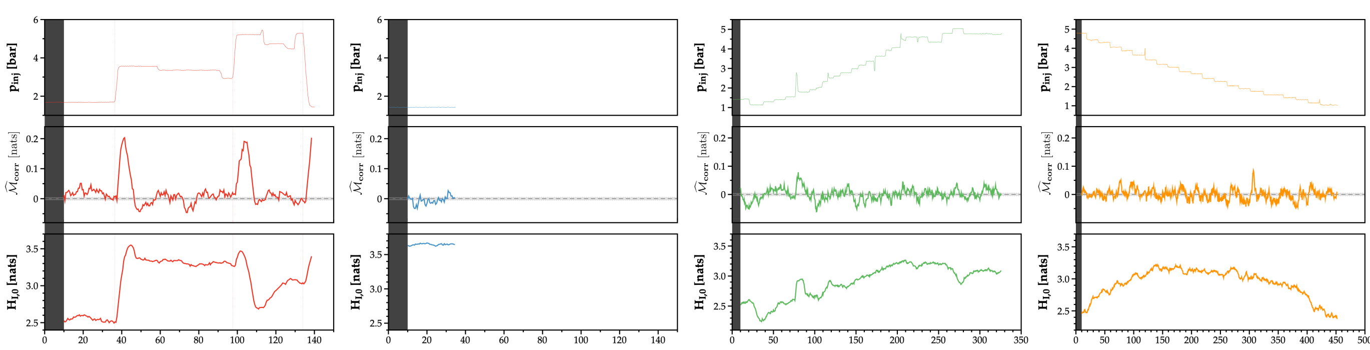

Figure 6. Results for the corrected memory traces $\widehat{\mathcal{M}}_{corr}$ [nats], and informature withing the pre-defined time window of 10 [s] $H_{I,0}$ [nats] for a number-weighted distribution of events.

Fig. 6 shows that in the first case, sudden changes in the injection pressure that alter the spray dynamics through a significant change in droplet velocity not only change the amount of information, as it produces spikes in the memory trace marking transformational changes in the spray. This demonstrates the ability to predict sudden changes in the spray using a corrected memory trace.

The reference case (2) indicates that we should expect oscillation around $\widehat{\mathcal{M}}_{corr} \sim 0$ for stabilized operating conditions. However, when we gradually changed the spray, slowly increasing (3) or decreasing (4) the injection pressure, the memory trace had a higher amplitude of oscillations, but also around zero. It seems that the spray, analogously to an infant, is changing, but "parents" do not notice the difference. However, when combined with informature evolution, we can capture the induced transformations. This means that developing a memory trace implies not only the mutual information between subsequent events within a time window but also close monitoring of the corresponding informature in its extensive format. The final paper will contain a higher diversity in the induced changes in spray characteristics, using more variable injection pressure profiles and measurement positions.

5. Concluding Remarks

This study advances spray diagnostics by introducing a fundamentally new way of interpreting measurements that treats laser-based observations not as static statistical outcomes but as evolving informational processes endowed with memory. By framing spray characterization within an infodynamic perspective, this study departs decisively from the prevailing paradigm dominated by time-averaged descriptors and distribution moments, and instead positions information itself as a primary physical observable alongside size and velocity.

The results demonstrate that conventional descriptors, such as the mean diameter or mean velocity, are useful but incomplete unless we also include in the spray characterization a measure of the diversity of drop dynamics with the informational state of the spray that can undergo substantial transformation. The introduction of differential informature as an intensive infodynamic quantity reveals changes in the spray structure and diversity that are invisible to classical statistical moments. This finding has deep implications, as it shows that commonly used convergence or stationarity criteria in laser diagnostics may be insufficient or even misleading when the spray evolves during the measurement process.

Equally significant is the introduction of a corrected memory trace $\widehat{\mathcal{M}}_{corr}$ as a quantitative measure of the temporal dependence in spray measurements. By explicitly distinguishing genuine physical memory from spurious correlations arising from finite sampling, the proposed method provides, for the first time, a robust operational definition of the measurement memory in spray diagnostics. The observed spikes and patterns in the corrected memory trace, combined with the informature for the considered time window, offer a clear signature of transformational events in the spray, whereas its near-zero baseline under steady conditions establishes a meaningful reference informational macrostate. This capability represents a major step forward for real-time diagnostics, enabling the detection of regime changes as they occur rather than retrospectively through post-processed statistics.

Beyond its immediate application, the framework proposed in this study has broader conceptual implications. It reframes the act of measurement itself: a spray measurement is no longer a passive accumulation of independent events but an active temporal construction in which past interactions between flow, particles, light, and instruments leave measurable traces in the present. In this sense, memory is not an abstract metaphor but a quantifiable physical property that emerges from the measurement process. This perspective aligns laser diagnostics more closely with contemporary views of complex systems, where history, transformation, and information are inseparable from the dynamics.

The infodynamic temporal spray characterization layer introduced in this study is fully complementary to established laser diagnostic techniques and does not compete with existing metrics; rather, it augments them with a dimension that captures what has so far remained unmeasured: the extent to which the past persists in the present signal and how this persistence changes when the spray itself changes. The implications for model validation, sensor development, and control strategies are substantial, particularly for applications in which sprays operate under nonstationary or transient conditions.

In conclusion, this study establishes a new foundation for spray diagnostics by demonstrating that information and memory are not secondary analytical constructs but intrinsic properties of both sprays and their measurements. By making these properties measurable, this study opens a new research direction in laser diagnostics, in which sprays are characterized not only by what they are, but also by how they transform and "remember". This infodynamic viewpoint has the potential to redefine how experimentalists assess convergence, detect transitions, and ultimately understand sprays as complex evolving systems rather than static statistical ensembles.

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Nomenclature

C	Characteristic parameter
d	Droplet diameter [μm]
f	Relative frequency
F	Length of the future block

$H_{\Delta,j}$	Differential informature of j-weighted probability distribution [nats]
$H_{I,j}$	Informature of j-weighted probability distribution [nats]
I	Mutual information [nats]
k	Class or bin index
K	Total number of possible events
$\mathcal{M}_{corr}$	Corrected memory trace [nats]
n	Number of droplets in a class
N	Total number of droplets in a sample
p	Probability density
P	Length of the past block
P_{inj}	Injection pressure [bar]
$\mathcal{Q}$	Quantization operator
t	Time [s]
u	Droplet velocity [m/s]
w	Weighted relative frequency
$\mathcal{W}$	Sequence of consecutive events
W	Number of consecutive events
X	Quantized measurement event
	Greek Symbols
ΔC	Bin size of a characteristic parameter
δt	Inter-arrival time [s]
	Superscripts
C	Characteristic parameter
d	Diameter-related
$F, +$	Future block
$P, -$	Past block
u	Velocity-related
ω	Time-window
	Subscripts
C	Characteristic parameter
$corr$	Corrected
d, D	Diameter-related
inj	Injection
j	Weighting probability distribution index
k	Class or bin index
$perm$	Permutation

P, F	Past and future blocks
$real$	Real data
u	Velocity-related
U	Velocity-related
	Acronyms
DSDn	Drop Size Distribution
DVDn	Drop Velocity Distribution
SMD	Sauter Mean Diameter

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