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Investigation of LDV signal evaluation methods by offline data analysis to reduce the measurement uncertainty

Untersuchung von LDA-Signalauswerteverfahren durch Offline-Datenanalyse zur Verminderung der Messunsicherheit

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Abstract
Laser Doppler velocimetry (LDV) is an established method for measuring and examining flow velocities and flow profiles. To date, several different LDV methods have been developed and tested in depth. Typically, the flow velocity and its measurement uncertainty are determined by statistical measures (mean value and standard deviation) making use of a large amount of LDV signals – so-called bursts. For this purpose, the Doppler frequency shift of the single LDV bursts is determined in situ since storing the complete time signal has not been possible. However, streaming data directly into an internal memory core is now possible. This is due to the availability of low-cost and fast memory devices – like solid state devices (SSD) – as well as fast analog-to-digital converters. Thus, the signal in the time domain does not need to be analyzed during the measurement but can also be evaluated afterwards. This opens the opportunity of using recursive and adaptive algorithms to further reduce the measurement uncertainty and examine the source of systematic errors as well as to investigate each single evaluation step. Especially in the case of a small number of LDV bursts – as for example for flow profiles in the vicinity of boundary layers – the determination of the flow velocity is not reliable every time. This increases the demand placed on a detailed analysis of the complete time signal and the corresponding measurement uncertainty. In this paper, an algorithm based on short-time Fourier transformation (STFT) is used to provide a single burst analysis. Thus, the effective number of detected events is increased so that the statistical measurement uncertainty can be reduced, and the temporal resolution of each individual event is also increased. To demonstrate these advantages, three different situations are investigated in this paper.

Introduction
Different methods for signal investigation have been examined in the past. They comprise techniques in the time domain [Agrawal 1984, Czarske 1993], the spectral domain [Deighton 1971] and the burst/real-time spectrum analyzer [Ibrahim 1992, Lading 1987, Meyers 1987]. Additionally, wavelet transformations have been used to refine the Doppler frequency determination [van Maanen 1999, van Maanen 1996, Nobach 2001]. The reason for there being so many different approaches for evaluating signals is as follows. It is that analyzing signals recorded with a laser Doppler anemometer are mainly used to obtain the Doppler frequency shift, and thus the spectral information is needed. In the spectrum of the signal, no temporal information of the signal is given. However, for a proper data analysis, a signal coming from a single particle in the measurement volume is required [Nobach 2002]. Thus, only a chunk

of the time signal, comprising a single burst, should be analyzed at a time. To find this chunk of time, temporal information about the signal is also needed besides spectral data. Therefore, different types of transformations – like the STFT or various types of wavelet transformations – have been established. They mainly differ in the way they compromise between the temporal and spectral resolution as can be seen in the schematic diagrams in Figure 1. There is another advantage of analyzing each individual burst instead of evaluating just chunks in time without the knowledge about the number of events occurring within that chunk. This advantage is the fact that the effective number of detected events is maximized, and thus the statistical uncertainty is reduced.

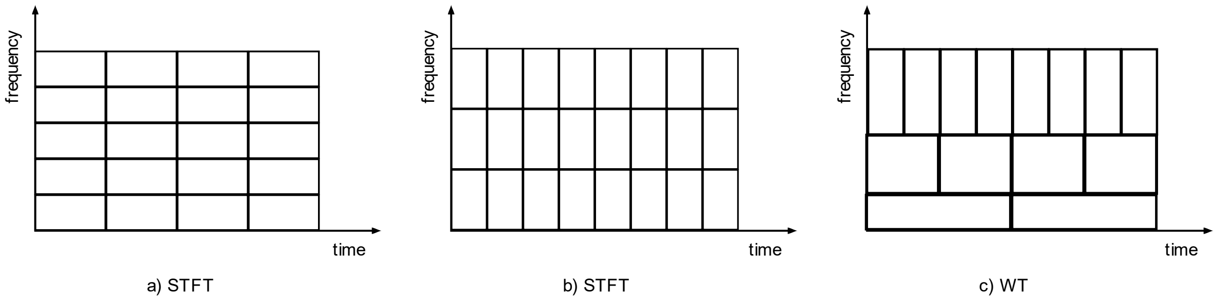

Figure 1: Schematic diagrams of the resolution for the spectrogram of: (a) STFT with high spectral resolution, (b) STFT with high temporal resolution, (c) wavelet transformation (WT) where the resolution is changing

In the first section of this paper, the general principle of the proposed algorithm is given. In section two, the algorithm is applied to three different systems: (A) a velocity reference, (B) a water flow and (C) an air flow with high dynamics. Section three discusses the information gained and summarizes the conclusions.

1. General principle of the evaluation algorithm

In the following, the general principle of the evaluation algorithm used in this paper is described. The availability of low-cost and fast memory types allows the data to be streamed into an internal memory core. This in turn allows an offline analysis. However, due to high recording rates, the size of the recorded data files is often quite large and causes problems for the evaluation. To circumvent this problem, the complete data stream is divided into chunks of a defined length where each chunk is evaluated on its own. Obviously, a signal in the time domain has different sections depending on the situation in the measurement volume. Three main situations are to be considered:

- There is no particle in the measurement volume so that only noise is recorded.
- There is exactly one particle present so that a clear signal is recorded.
- There are multiple targets reflecting light back to the sensor. Thus, an interaction of these signals must be considered.

To obtain a reliable Doppler frequency shift, only the situation where one burst is present in the signal should be used. Thus, the goal for the algorithm must be to detect a single burst with a following single burst analysis. For signals with a high signal-to-noise ratio, the single burst detection might be done using only a simple amplitude criterion. However, for signal amplitudes in the order of the background noise, this is not a reliable solution. In this paper, the STFT is used to analyze the signal in time and frequency domains in parallel.

One example of the main steps of the algorithm is shown in Figure 2. Figure 2 (a) depicts a typical time domain signal (what is shown is one chunk of the complete time domain signal). In Figure 2 (b), the corresponding spectrogram of the STFT with a relatively high temporal resolution of 12.8 μs and thus a low spectral resolution is given. Since the STFT of a signal is used to determine the temporal and the frequency characteristics of a signal at the same time, there is always a compromise for the resolution in these two domains. Thus, depending on the system under investigation, the resolution chosen for the STFT must be adopted. After having calculated the STFT, a cross section through the maximum of the spectrogram parallel to the time axis (shown in (c)) is used to find the minima and maxima. The maxima represent the detected bursts (including the corresponding timestamp), while the neighboring minima are used as timestamps to isolate the single bursts for the complete signal in the time domain. Figure 2 (d) shows a single burst which is ready for the analysis. The Doppler frequency shift of a burst is determined by a simple FFT and a parabolic peak interpolation for the peak finding. Additionally, the burst in the time domain is fitted by a Gaussian profile to refine the timestamp of the detected event. This is also undertaken to determine the burst width or transient time and amplitude allowing the burst arrival time to be detected precisely.

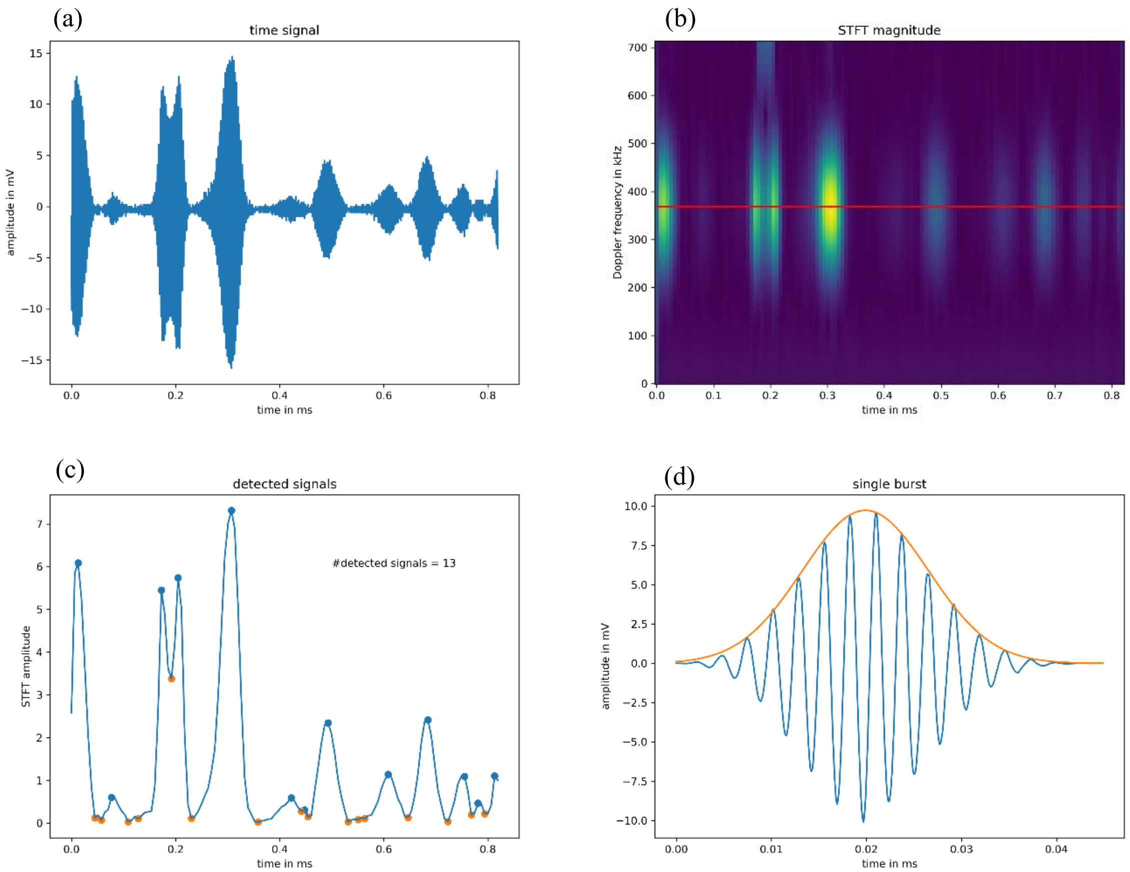

Figure 2: General principle of the evaluation flow: (a) signal in the time domain, (b) spectrogram from the STFT, (c) cross section through the spectrogram along the red line in (b) and burst finder by peak detection, (d) single LDV burst

After having evaluated all single bursts in this way and depending on the examined system, the data can be filtered with respect to certain criteria. However, filtering data also corresponds to a reduction of the amount of data and thus must be done with care. In this paper, three criteria have been used:

(1) For systems comprising only one well-known flow velocity – like a velocity reference – the outliers can be removed. A three-sigma filter has been used for the first example (A). For other systems under investigation, an appropriate bandpass filter is used.

(2) Due to different reasons – like small amplitude or multiple bursts – fitting the envelope of a burst is not always possible or physically reasonable. In these cases, an evaluation of the signal seems to be problematic and thus these signals are ignored. This has been implemented by setting the transient time for these cases to 0 s and taking only signals into account that have a positive transient time.

(3) LDV bursts having a small signal-to-noise ratio are hard to detect. It is most likely that these bursts contribute to a larger measurement uncertainty. Thus, it is reasonable to introduce an adaptable burst amplitude criterion to investigate the influence of these bursts on the measurement uncertainty. Of course, the value of this limit must be adopted for each system, and it is an essential parameter for the data rate and thus the statistical uncertainty.

2. Offline data evaluation

In the following, the proposed algorithm has been applied to three different systems with different challenges in the evaluation. In the first example, a rotating disc was used as a velocity reference. This system is well known and thus can be used as a first validation step using a 1dLDV. In the second example, a water flow within a closed loop was used to examine a real particle flow with a two-channel LDV profile sensor. In the third example, an air flow at the output of a de Laval nozzle was examined with a LDV profile sensor to investigate the flow in a different medium with higher dynamics. The results are compared to the implemented algorithm for online analysis which is based on the evaluation of time chunks of defined lengths. The length of a chunk is chosen by estimating the expected flow velocity and the geometry of the measurement volume. The chunk evaluation is triggered by an amplitude criterion.

(A) Velocity reference

To evaluate the proposed algorithm, a set of offline test data from a velocity reference was used. Therefore, a disc that was sparsely covered with particles was rotated with a nominal surface speed of about $v_{ref} = 2.2\ \frac{\mathrm{m}}{\mathrm{s}}$. Figure 3 shows the results of the evaluation. Figure 3(a) depicts the number of detected events per chunk. Due to the rotation of the disc, a self-similarity corresponding to the rotating speed of the disc can be observed. Figure 3(b) shows the histogram of the Doppler frequency shift also giving the mean value and its standard deviation as well as the number of detected events. Figure 3(c) gives the temporal behavior of the determined velocity confirming the nominal speed. The maximum width of the measurement volume was $d = 56.5\ \mu m,$ which – together with the mean velocity of the particles – resulted in a maximum stay time of a particle in the measurement volume of $\Delta t = 25.7\ \mu s$. This result fits well with the transient time shown in Figure 3(d). Since the particles on the disc were placed randomly, most of them did not pass the exact center of the measurement volume. The corresponding transient time was therefore below the maximum stay time. The temporal separation of successive bursts was $\Delta t = (44 \pm 21)$ µs. In combination with Figure 3(d), it can be observed that most of the detected events are single particle events. In order to investigate the influence of multiple particle events, an additional evaluation was performed filtering these events. However, the influence on the result was negligible.

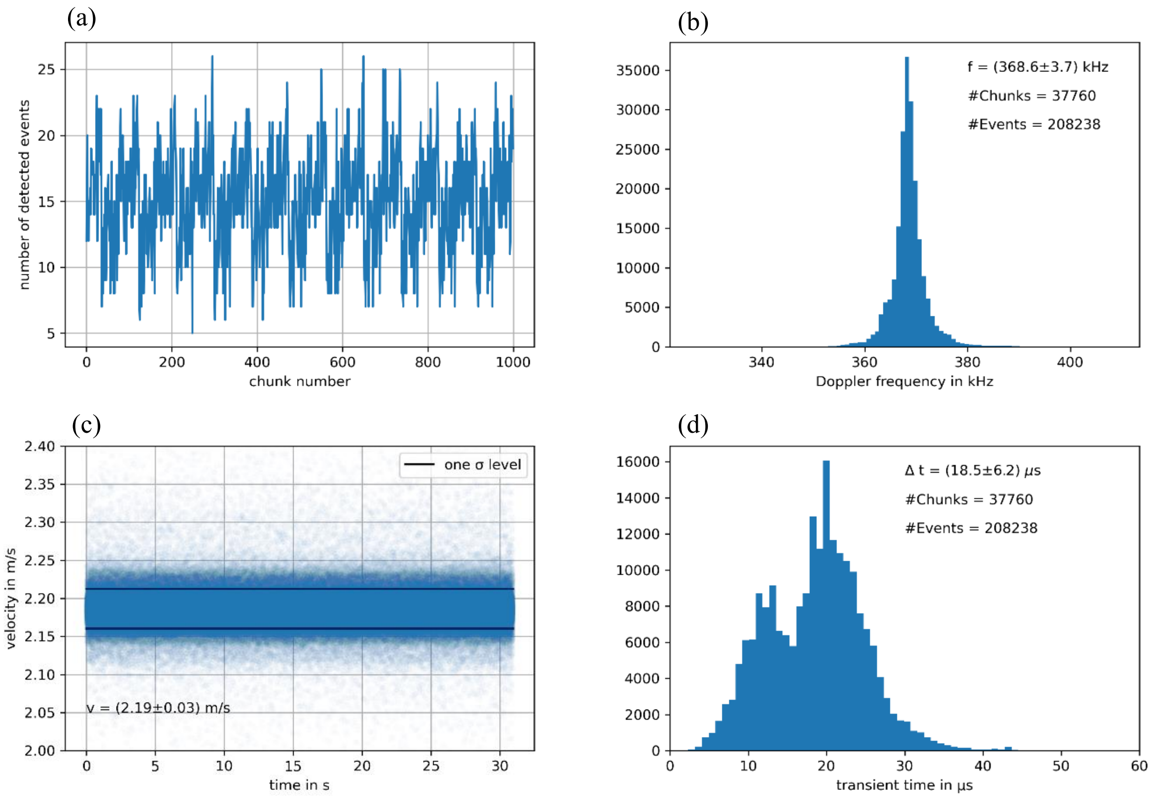

Figure 3: Offline data evaluation from the velocity reference: (a) number of detected events per chunk for the first 1000 chunks, (b) histogram of the Doppler frequency shift, (c) velocity time diagram, (d) histogram of the transient time

Comparing the number of events detected with this algorithm – here 208,238 events in about 30 seconds (data rate: $6.9\ kHz$) – with the actually implemented evaluation algorithm which detected 201,896 events (data rate: $6.5\ kHz$) in the same time, the amount of data for the evaluation can be slightly increased. This results in a minor optimized statistical uncertainty (for the one σ level): $u_v = 4.36 \cdot 10^{-5}\,\frac{m}{s}$ compared to $u_v = 4.45 \cdot 10^{-5}\,\frac{m}{s}$. Since the system is well known, and the recurring signal is well defined, it is not astonishing that the results are very similar.

(B) Water flow

In the following, the results from a real water flow experiment are shown. The nominal flow velocity should be in the region of $v_{nom} = 0\,\frac{\mathrm{m}}{\mathrm{s}}$ to $v_{nom} = 1\,\frac{\mathrm{m}}{\mathrm{s}}$. The measurement was performed with a two-channel LDV profile sensor. The profile sensor used the ratio between the two Doppler frequencies to determine the burst position within the calibrated measurement volume which was positioned in the vicinity of a wall. The results of the measurement using the conventional as well as the proposed single burst algorithm are shown in Figure 4. The data rate in this example is in the same order of magnitude for both algorithms, which is because events are only registered if they occur in both channels. As can be seen in Figure 4 (a) - (c), the occurrence of events for negative positions (near the wall) is decreasing. The corresponding velocity is also decreasing as would be expected in the vicinity of a wall. The mean velocity weighted with the number of bursts detected highlights this behavior. Comparing Figure 4 (a) to (b), both algorithms show similar results. However, the single burst algorithm additionally provides information about the burst itself like the transient time shown in Figure 4 (d). The maximum width of the measurement volume is $d = 32.5\ \mu m$, which together with a velocity of the particles – varying between $|v| = 0.1\ \frac{m}{s} - 0.65\ \frac{m}{s}$ – result in a maximum transient time of a particle through the measurement volume between $\Delta t = 325\ \mu s - 50\ \mu s$. This result fits well with the transient time shown. Obviously, slower particles show larger deviations since they stay longer in the measurement volume, and the transient time approaches the chunk length (in this case $650\ \mu s$). This is a challenge for each algorithm since these bursts are truncated and complete bursts cannot be evaluated.

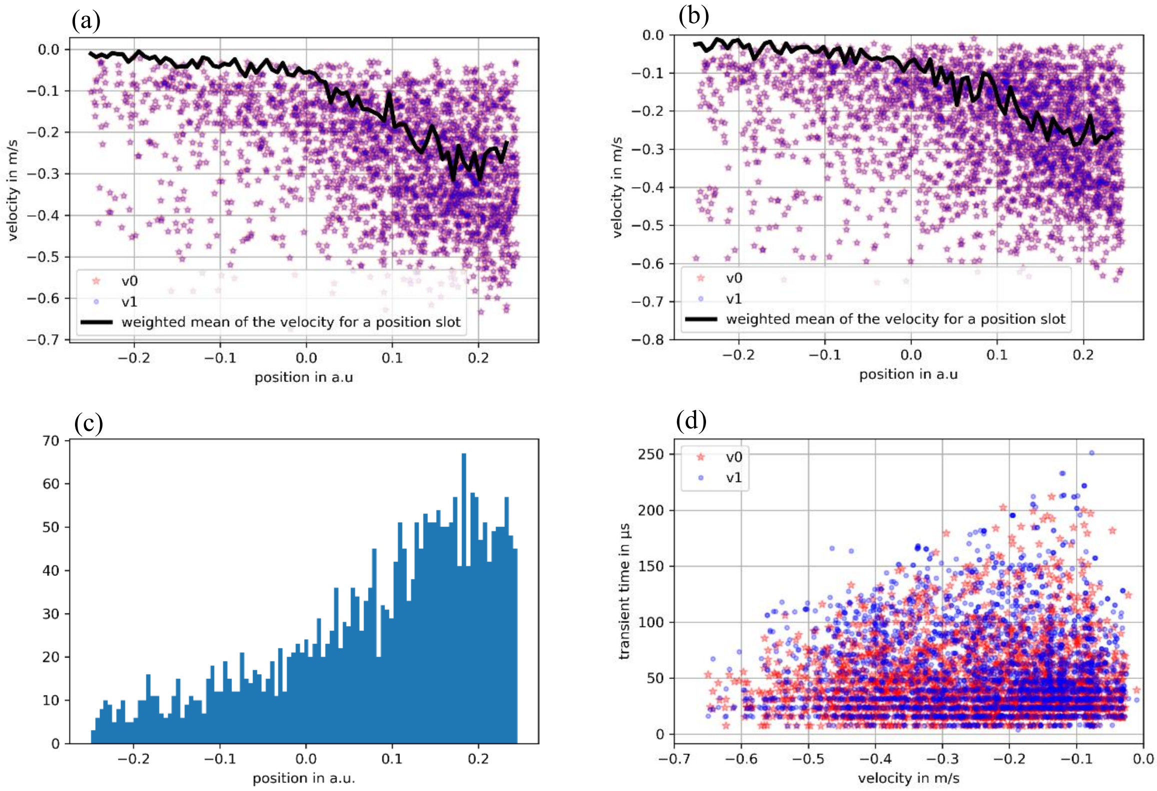

Figure 4: Offline data evaluation from a water flow: velocity position diagram with (a) conventional algorithm, (b) the proposed single burst algorithm, (c) histogram of the position of the event with the proposed single burst algorithm, (d) transient time velocity diagram

Another effect can be observed in Figure 4 (d): the quantization of the transient time, which is related to the compromise of the temporal and spectral resolution of the STFT. Compared to the other presented signals in (A) and (C), the signal-to-noise ratio in this case is smaller. In order to detect a burst in the time signal, the spectral resolution has to be increased resulting in a reduced temporal resolution so that the quantization becomes visible.

(C) Highly dynamic air flow

Finally, an air flow with a high dynamic range in the expected Doppler frequency shift is examined. For this purpose, a de Laval nozzle with a magnetic switch is manually triggered during the measurement. Due to the high pressure within the center of the air flow, condensation takes place resulting in a self-seeding of the flow with water droplets. The nominal flow velocity at the outlet of the nozzle should instantly change from $v_{nom} = 0\ \frac{\mathrm{m}}{\mathrm{s}}$ to $v_{nom} = 450\ \frac{\mathrm{m}}{\mathrm{s}}$ and then slowly decay. Figure 5 shows some of the results. In (a) the measurement setup with the crossing laser beams is shown. In Figure 5(b), the 2d histogram of the Doppler frequency shift over time is shown. It can be observed that in the short time after opening the nozzle, many high-speed events are detected which decrease with time. In Figure (c), the velocity time diagram shows the increase of the velocity up to $v = 450\ \frac{m}{s}$ at $t \approx 0\ s$ as well the exponential decay after the trigger. The reason for the measured velocity not dropping below a value of $v \approx 100\ \frac{m}{s}$ might be that a certain flow velocity is needed for the self-seeding. Below this velocity, the condensation does not take place and thus no particles are present for the measurement. After about $t = 2\ s$, the nozzle is closed. The complete velocity bandwidth can be measured since the measurement volume is much bigger than the diameter of the nozzle so that also particles at the edge of the air beam are detected. In Figure 5(d), a histogram of the transient time is shown. The maximum width of the measurement volume is $d = 176.5\ \mu m$, which together with a velocity of the particles – varying between $v = 100\ \frac{m}{s} - 450\ \frac{m}{s}$ – result in a maximum transient time of a particle in the measurement volume between $\Delta t = 1.765\ \mu s - \ 0.39\ \mu s$. This fits well to the result in Figure 5(d).

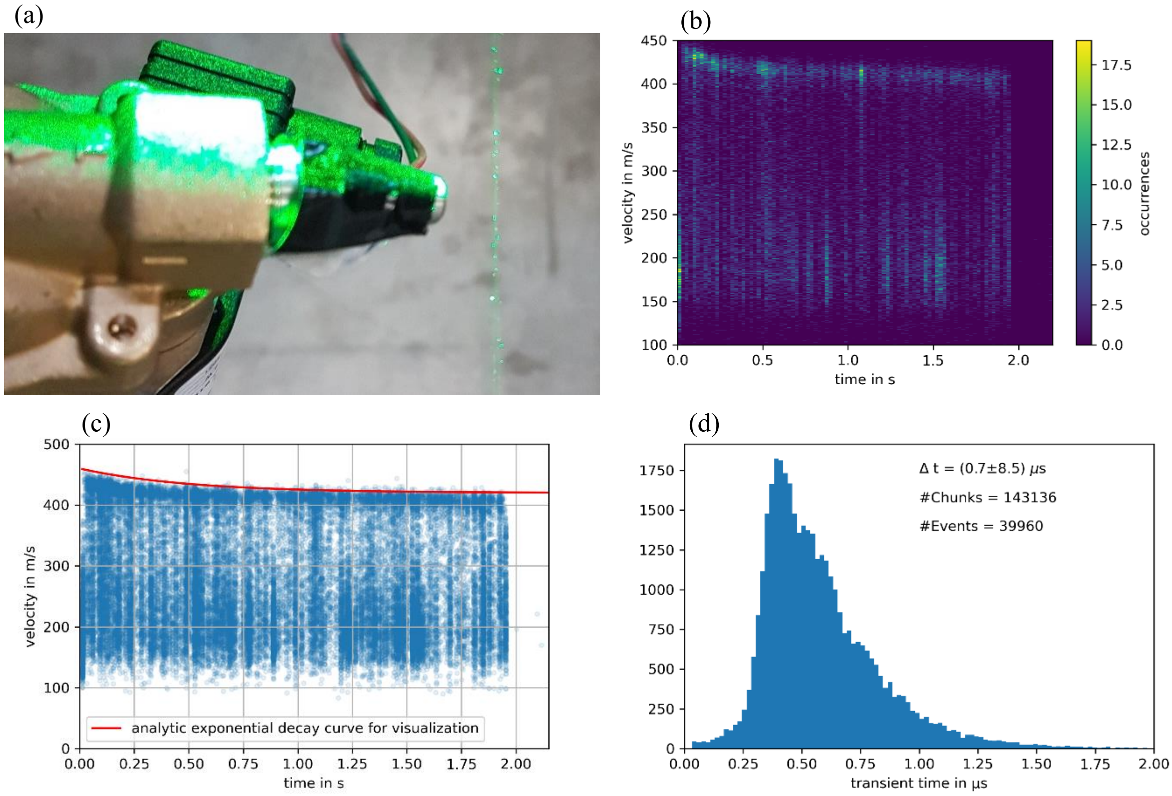

Figure 5: Offline data evaluation from an air flow with a high dynamic range: (a) measurement setup, (b) 2d histogram of the velocity over time, (c) velocity time diagram, (d) histogram of the transient time

Comparing the number of detected events, the presented single burst detector finds about 40,000 events (data rate: $20\ kHz$) while the algorithm that has been used so far finds only about 14,000 (data rate: $7\ kHz$). Thus, in this example again, a higher data rate and thus a reduction of the statistical uncertainty ($u_v = 0.47\frac{m}{s}$ compared to $u_v = 0.78\frac{m}{s}$) as well as a higher temporal resolution can be achieved.

3. Discussion and conclusion

In this paper, an algorithm using the STFT as a mechanism to isolate single bursts has been presented. Since the signal is processed directly and only the Doppler frequency shift is stored for the online evaluation, the offline analysis offers a great deal of potential to investigate the time signal in much more detail with for example a single burst evaluation. The proposed algorithm is used to successfully evaluate offline data from an LDV in three different situations. Due to the evaluation of each individual burst with the optimum amount of data points in the time domain, especially in the third example, the number of detected events is increased significantly. This occurred with respect to the conventional algorithm used for online evaluations. The thereby reduced statistical uncertainty as well as the temporal resolution already demonstrate that the single burst evaluation algorithm in the current state is suited even for high-speed situations with high dynamics. For the example in a water flow, the advantages of the single burst algorithm are not that obvious yet. The reason for this is that due to the correlation of the two channels, a large amount of data is neglected. Amongst other things, the implementation of special algorithms dealing with this challenge should be an essential part of work in the future. Investigating further situations and adopting the algorithms to other systems – like phase doppler velocimeters – are just as important. To date, the proposed algorithm does not seem to be suited for online usage since the computing time for the single burst finder is quite large. But if the measurement situation is stable, it can be used as an “in-advance” measure to get an idea about the data rate, the signal amplitude, the dynamics, and the Doppler frequency shift distribution that can be expected within the actual measurement. This information can be used to set up the evaluation parameters for the online measurement. Such a combination of off- and online data evaluation might be used to optimize the measurement accuracy and might also enable an easy adoption of the evaluation routine to customers’ individual needs.

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