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A Scheme for Resampling, Filtering, and Subsampling Unevenly Spaced Laser Doppler Anemometer Data[1]

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Laser Doppler Anemometry (LDA) has proved a powerful tool for quantifying fluid turbulence and is increasingly being applied in fields such as fluvial sedimentology and geomorphology. When operated in the burst-signal processing mode, high-frequency velocity fluctuations are measured at irregular time intervals. In many situations, there is a need to transform these data to obtain evenly spaced velocity values but at a lower frequency. However, clear guidelines for this type of data processing are lacking. Three steps are necessary in order to transform the original files into evenly spaced data: (1) resampling at the average sampling rate, (2) low-pass filtering with half-power frequency adjusted to the final sampling frequency, and (3) decimating at the desired frequency. The decision taken at each step will affect the resulting signal and may cause, if not assessed carefully, severe problems in the signal such as aliasing errors. This paper examines each stage of data processing and details the advantages and drawbacks of different techniques in relation to the effects on turbulence statistics (variance, instantaneous shear stress, etc.). A standard method and specific guidelines are finally proposed.

KEY WORDS: time-series analysis, turbulence statistics, aliasing.

INTRODUCTION

During the past few years, laser Doppler anemometry has been used extensively in fluid dynamics (Fu, Tindal, and Yianneskis, 1991; Shahnam and Morris, 1991), and sedimentology and fluvial geomorphology (Agrawal and Aubrey, 1992; Best and Leeder, 1993; Nelson, McLean, and Wolfe, 1993; McLean, Nelson, and Wolfe, 1994; Bennett and Best, in press). Laser Doppler anemometry (LDA) offers several important advantages over other techniques of turbulence measurement, principally its high spatial and temporal resolution and nonintrusive behavior, which make it attractive in research on many important and unresolved problems involving the interrelationships between flow and sed-

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iment transport. In the earth sciences, it has become increasingly important to examine the details of turbulent boundary layer structure in order to understand the interactions between flow, sediment transport, and bedform development (Leeder, 1983; Best, 1993).

Laser Doppler anemometry (LDA), when operated in the burst-signal processing mode, measures velocity only when a seeding particle is detected and validated in the measuring volume. Therefore, the time interval between two consecutive velocity measurements is controlled only by the seeding process, which is random. In many situations, there may be a need to transform the original signal into a set of evenly spaced data as the irregularity in data spacing can be problematical for the subsequent analysis.

Firstly, although it is possible to carry out time-series analysis (e.g., autocovariance, spectrum) on randomly sampled data (Parzen, 1984; Press and Rybicki, 1989; Lee and Sung, 1994), these statistical techniques seldom are available in existing software (e.g., Dantec, 1992). Secondly, resampling LDA data at a common frequency may be essential in order to compare the turbulent structure of the signals. Indeed, the temporal resolution of LDA signals varies with distance from the wall and with flow velocity (Wei, 1987). Hence, LDA signals measured at different lateral positions and in changing flow conditions are characterized by large variations in sampling rates and this further complicates statistical comparisons. For example, high sampling rates give rise to increasing autocorrelation in the first lags (Robert, Roy, and De Serres, 1993) and can result in a higher order autoregressive model. Therefore, signals with similar turbulent behavior but different sampling rates may be described erroneously by different models. To avoid this problem, the original signal must be transformed at a lower, common (evenly spaced) sampling frequency. Finally, turbulent data may be related to other types of data of lower sampling frequency, for instance instantaneous sediment transport measured with video images (30 frames/sec). In these situations, resampling the LDA data at a lower (evenly spaced) sampling rate is desirable to eliminate high-frequency fluctuations which may disguise the more important lower frequency turbulent fluctuations.

Data processing to achieve such a lower frequency regular signal consists of resampling, filtering, and subsampling the original LDA velocity time series. Note that in this paper resampling will designate the process of bringing unevenly spaced data to a regular interval whereas either subsampling or decimating will refer to reduction of the sampling rate of an already regularly spaced signal. Although there exists a comprehensive literature on digital sampling and filtering (see for example Oppenheim and Schafer, 1975; Hamming, 1977; Bendat and Piersol, 1986), no robust rules for unevenly spaced data resampling or subsampling are available. This situation forces many LDA users to build their own procedures (e.g., Wei and Willmarth, 1989). This results in several difficulties: (1) because of the paucity of theoretical background on resampling/

subsampling unevenly spaced data, clear statistical rules governing such data manipulations do not seem to exist, (2) the ambiguity surrounding this problem leads to different ways of resampling and filtering, hindering comparisons between studies, and (3) the effects on turbulence statistics of post-acquisition data processing are largely unknown. This makes it difficult to estimate what is left of the original signal in published data. This point is underestimated greatly and the effects of the various steps of data processing must be evaluated in order to reach sound conclusions.

In view of these problems, this paper examines various strategies of processing unevenly spaced LDA data, describes their effects on turbulence statistics (such as turbulence intensity, power spectra, instantaneous Reynolds shear stress, coherent structures time scale), and proposes a methodology to facilitate comparison between studies.

THE USE OF ORIGINAL RANDOMLY SAMPLED SIGNALS OR OF RESAMPLED SIGNALS

Original Signals

Using original signals in the burst-signal processor mode implies working with unevenly spaced data. The moments can be estimated by residence-time weighting in order to avoid biasing effects (Buchhave, George, and Lumley, 1979) but care must be taken to provide a high, uniform seeding density in the fluid as the output statistics are a function of the particle arrival rate (Edwards and Jensen, 1983). However, the drawbacks of using randomly sampled LDA signals are important. Time-series analysis is complicated by randomly sampled data and the literature on this subject is scarce, albeit increasing (Parzen, 1984; Lee and Sung, 1994). It is important to highlight that if time-series analysis is conducted with data resampled at regular interval, then *all* the statistics, including first- and second-order moments, must be recomputed from the new resampled signals. Also, LDA signals may contain noise contamination either from optical sources, photodetection effects or electronic system sources (Durrani and Greated, 1977). It is possible to remove this noise with a notch filter in situations where the noise is concentrated in a narrow frequency band, but this demands resampling in order to use regularly spaced data which are required in digital filters (Hamming, 1977).

The choice of whether to work with the original signals is dependent on the aims of the study. If only the mean and variance are required, working with the original signal offers the advantage of avoiding several stages of data processing (exporting single files, resampling, filtering, etc.). If a more detailed analysis is needed, for example in order to examine the turbulent flow structure, then using regularly spaced data may prove necessary.

Regularly Spaced Signals

Before examining methods of transforming unevenly spaced data into regularly spaced data of lower sampling frequency, it is essential to consider the effects of aliasing in sampling. Aliasing is basic to sampling data at equally spaced intervals and corresponds to the folding of signal variance at frequencies higher than the Nyquist frequency ($f_N = f_D/2$, where f_D is the sampling rate) into lower frequencies (Bendat and Piersol, 1986). Folded frequencies thus will seem confused within the variance of data in the lower frequency range (Fig. 1). The only practical way to avoid aliasing errors is to ensure that all the information contained at frequencies higher than the Nyquist frequency is removed by low-pass filtering *prior* to resampling (Bendat and Piersol, 1986).

Aliasing problems principally occur during analog to digital conversion, where an analog low-pass filter is required, or during decimation of a regularly spaced digital signal, where a digital low-pass filter is needed (Bendat and Piersol, 1986). Our problem of resampling unevenly spaced digital data does not fall into either of these categories, yet it may entail some aliasing effects, which must be avoided. This problem is more complex than it seems and its careful examination is necessary if an optimal decision is to be taken. Consider an original signal with an average sampling rate (number of data/length of the record) of 400 Hz. The objective, for the sake of argument, is to obtain regularly spaced data at a lower frequency, say 40 Hz. According to the sampling theorem, we would have to remove all the information contained in frequencies above the Nyquist frequency (f_N = 20 Hz in this example) *prior* to resampling. This operation involves application of a low-pass filter to the original signal but digital filters can be used only on equally spaced data (Hamming, 1977). There-

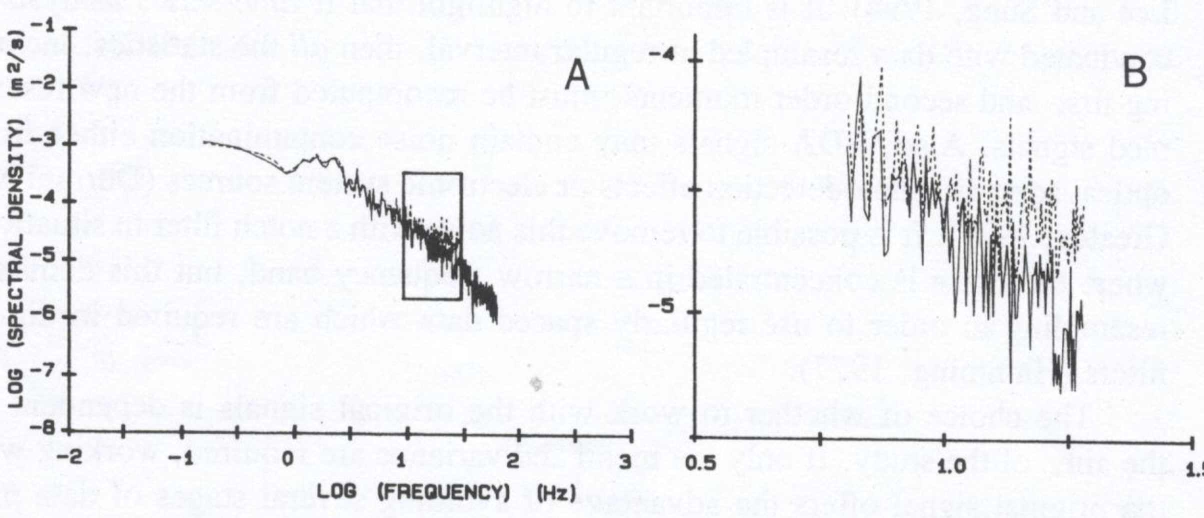

Figure 1. A, Example of aliasing: signal 2 is resampled at its average sampling rate, 856 Hz (solid line) and at 40 Hz (dashed line); B, blow-up showing folding of higher frequencies present near Nyquist frequency (f_N = 20 Hz) when signal is resampled at 40 Hz (dashed line).

fore, the signal first must be resampled at regular intervals before it is low-pass filtered. Only then is it possible to decimate the signal at the desired frequency.

However, this method may have problems because aliasing errors will occur during the first step (i.e., resampling) as all the variance in the resampled signal contained in frequencies higher than f_N will be folded back into frequencies lower than f_N. This therefore demands that the resampling rate is high enough so there is virtually no variance left above the Nyquist frequency of the resampled signal or that the resampling rate be greater than the original average sampling rate. The latter solution, however, may prove impractical with high original average sampling rates because of subsequent problems of computation with extremely large datasets. A more realistic approach is to use the fact that there is less and less variance left as frequency increases. Therefore, even if the original signal is resampled at its average sampling rate (Wei and Willmarth, 1989), expected aliasing will be limited to frequencies close to f_N (see Fig. 1). In other words, negligible aliasing errors may be assumed in the range of frequencies lower than the subsampling rate Nyquist frequency. The corollary of this is that original signals must be collected at average sampling rates high enough to allow the assumption of negligible aliasing at low frequencies to be true. This will ensure that the data density (sampling rate times the flow characteristic time scale) is high enough for the resampling method to work (Edwards and Jensen, 1983).

Once the resampling rate has been established, a decision must be made on the resampling technique. Two techniques are examined here: linear interpolation and ''windowing.'' Linear interpolation is used widely (Wei and Willmarth, 1989; Dantec 1992) and offers two principal advantages, namely simplicity and that, in relation to aliasing errors, it creates a damping of high-frequency fluctuations (Wei, 1987) which reduces folding in the low frequencies (Fig. 2A). The principal disadvantage of linear interpolation is that new velocity data are generated which are not present in the original signal. An alternative method to linear interpolation is ''windowing'' which entails selecting velocity values in the original signal with arrival times closest to the regularly spaced time lags. This technique is similar to the stretching/compression procedure (Veynante and Candel, 1988) with the difference that not all the data points are retained. The main advantage of windowing over linear interpolation is that only the truly measured velocities present in the raw signal are kept. Although windowing gives rise to small time errors which are equal to the difference between regular time lags and arrival times, this technique preserves most of the amplitude of velocity fluctuations, contrary to linear interpolation (compare Figs. 2A and 2B), but, as for stretching and compression, it shifts the resulting signal laterally on the x-axis.

Once the original signal has been resampled it may be low-pass filtered according to the desired subsampling rate. An extensive literature exists on

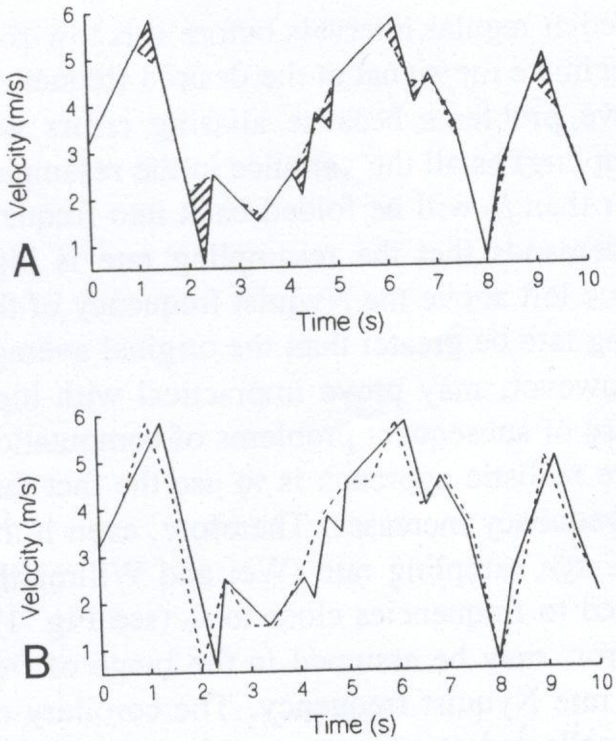

Figure 2. Effects of resampling at regular intervals randomly sampled (fictive) trace: A, by linear interpolation; B, by windowing. Solid lines represent original traces and dashed lines resampled traces. Shaded areas in A highlight losses of variance in high-frequency fluctuations.

digital filters (e.g., Oppenheim and Schafer, 1975; Hamming, 1977) and a wide selection of filtering designs is available. Two criteria particularly are important in the selection of filter: (1) it is desirable to avoid filters that will produce a reversal in polarity and create a 180° phase shift of the waves (Holloway, 1958). Running mean and exponential filters are examples of such phase shifting filters, and, (2) the design of the filter should allow both replicability and generality. The Gaussian smoothing function, $w(t)$, was selected in this study because it complies with both criteria. It is defined as:

$$w(t) = (2\pi\sigma^2)\ \exp\left(-t^2/2\sigma^2\right) \tag{1}$$

where σ is the standard deviation of the normal curve.

Ideally, a low-pass filter should preserve all the frequencies lower than the cutoff frequency (f_N in our situation) and remove all the information above that threshold. In reality, there exists a transition zone between the frequency where the filter starts affecting the amplitude of waves and the frequency where all the information is removed. This is illustrated by the frequency response of the filter which is defined as the ratio of the magnitude of the modified vector to the magnitude of the unit vector (Holloway, 1958). For the normal curve filter, the frequency response at a given frequency (f) is:

$$R(f) = \exp\left(-2\pi^2\sigma^2 f^2\right) \tag{2}$$

This frequency response has a long rolloff (i.e., a wide transition zone), which then necessitates a somewhat arbitrary criterion to estimate the proper standard deviation for use in (1) so almost all the information above f_N is removed. A suitable selection could be the "time constant type" filter that is used in Electromagnetic Current Meters (e.g., Marsh-McBirney ECMs) where the half-power period of the RC filter (where 50% of the variance is lost) is equal to six times the time constant of the instrument. Because the frequency response is equal to the ratio of magnitudes of the modified and original signals, the ratio of variances of the modified and original signals can be computed using the square of the frequency response, that is, a 50% loss in variance corresponds to:

$$[R(f)]^2 = 0.5; \qquad R(f) = 0.5^{1/2} \tag{3}$$

If we assume the subsampling interval to be equivalent to a ECM time constant, then the half-power frequency (f_{50}) is equal to $f_D/6$ (where f_D is the subsampling frequency). From (2) and (3), the standard deviation of the filter, σ (in seconds) then can be computed as:

$$\sigma = (\ln 0.5^{1/2}/(-2\pi^2 f_{50}^2))^{1/2} \tag{4}$$

Use of (2) and (4) shows that 0.2% of the variance will be left at f_N. Thus this filter completely eliminates variance at frequencies above f_N and severely reduces that at frequencies below but close to f_N. Although a less severe filter may be selected, the use of the Gaussian smoothing function again minimizes aliasing errors that may be present close to f_N of the subsampled signal.

The final stage in data processing is to decimate or subsample the filtered signal. Decimation of the *d*th order consists of keeping every *d*th data value and discarding all other values (Bendat and Piersol, 1986). When possible, it is preferable to use decimation rather than subsampling at a given frequency rate where further linear interpolation would be required. The selection of a subsampling rate is, once again, a function of the study objectives: higher subsampling rates will produce a larger signal frequency bandwidth. Ideally, *a priori* knowledge of the frequency band of interest for a specific problem is desirable to guide the selection of the subsampling rate. Additionally, because the sampling interval is known to affect some statistics, such as correlation (Robert, Roy, and De Serres, 1993), it is preferable to use a common decimation rate for all signals.

To summarize, three distinct stages are needed in order to transform an original irregularly spaced LDA signal into a regularly spaced signal of sampling frequency f_D. (1) Resampling either by linear interpolation or windowing at the average sampling rate of the raw signal, (2) low-pass filtering with half-power at $f_D/6$, and (3) signal decimation at the desired frequency, f_D. It is, however, then necessary to quantify how each of these stages affects the original signal.

EFFECTS OF RESAMPLING, FILTERING, AND SUBSAMPLING ON SELECTED EXAMPLES

In this study, we used a fibre optic LDA (DANTEC) with Flow Velocity Analyser (FVA) burst type correlation processors to examine the effects of resampling, filtering, and subsampling on velocity signals. A 161 mm focal length front lens was used with a beam separation of 38 mm and a measuring volume of 0.16 mm^3. Sampling rate was set through optimisation of the high voltage supply, seeding density, and burst threshold detection levels to produce sampling rates between 200 and 900 Hz. Data were collected using FVA computer software (DANTEC) which does not have a routine for unevenly spaced data. The LDA was used to measure the streamwise (U) and vertical (V) velocities in a 10 m long, 0.30 m wide recirculating flume. Seeding particles of titanium had a diameter of 1 μm. Flow depth (Y) was 0.16 m, Reynolds number 6520, and Froude number 0.12.

Two, 1-minute long samples from a turbulent flow over a smooth boundary will be examined here (Signals 1 and 2). Signal 1 was taken at a nondimensional height (Y_D) (height of measurement/mean flow depth) of 0.03 with an average sampling rate of 241 Hz whereas Signal 2 was measured near the water surface ($Y_D = 0.81$) with an average sampling rate of 856 Hz. In both situations, the thickness of the turbulent boundary layer ($\delta = 0.99\ V_f$, where V_f is the free-stream velocity) was $\delta/Y = 0.6$. Thus, Signal 1 is located in the turbulent boundary layer whereas Signal 2 is above it.

The subsampling rate has been fixed at 40 Hz, keeping in mind an eventual correlation of turbulence data with other types of data (e.g., sediment motion) of lower sampling frequency. Moreover, both original sampling rates (241 Hz and 856 Hz for signal 1 and 2, respectively) are higher than the final frequency, thus minimizing risks of aliasing. Using (3), the standard deviation of the normal curve filter for a subsampling rate of 40 Hz is 0.0199 sec.

The effects of the various steps of data processing on a portion of signal 1 are displayed in Figure 3. The results from the two resampling techniques (Fig. 3B, 3C) illustrate that only subtle changes in the shape of the time series are generated at this stage. However, filtering (Fig. 3D) clearly modifies the signal and removes all high-frequency fluctuations, permitting a better visualization of the lower frequency turbulent structure. The shape of the signal is virtually identical after the subsampling stage (Fig. 3E).

Variance

Table 1 shows the effects of each step (resampling, filtering, and subsampling) on the signal variance of the U (streamwise) and V (vertical) components together with results comparing the two different resampling techniques (interpolation and windowing). Resampling by windowing does not affect the variance

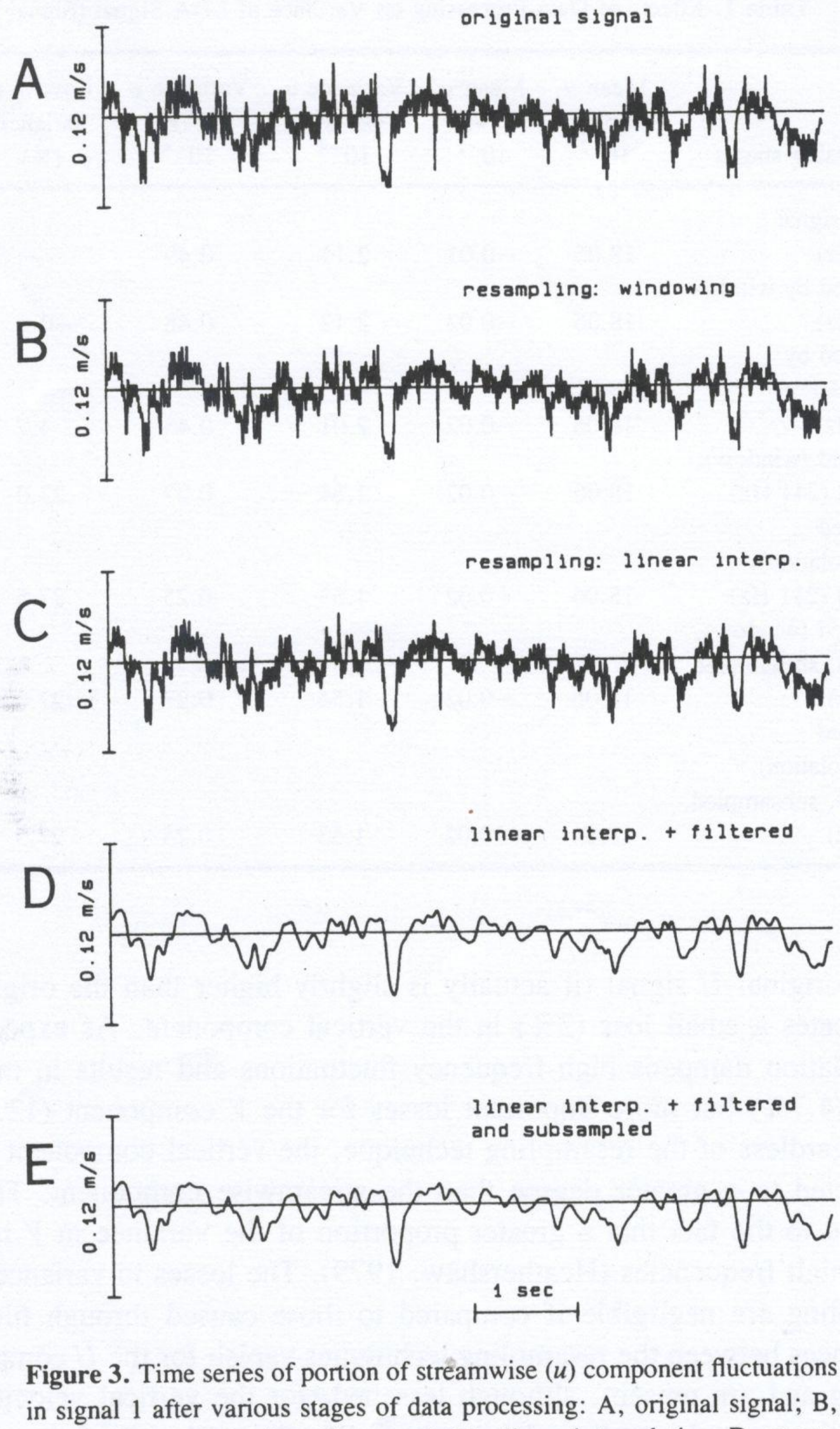

Figure 3. Time series of portion of streamwise (u) component fluctuations in signal 1 after various stages of data processing: A, original signal; B, resampled by windowing; C, resampled by linear interpolation; D, resampled by linear interpolation and filtered (σ = 0.0199 sec); E, resampled by linear interpolation, filtered, and subsampled at 40 Hz. Trace is 7 seconds long.

Table 1. Effects of Data Processing on Variance of LDA Signal (Signal 1)

Processing stages	Mean u (m/s) 10^{-2}	Mean v (m/s) 10^{-2}	Variance u (m^2/s^2) 10^{-4}	Variance v (m^2/s^2) 10^{-4}	Loss in u variance (%)	Loss in v variance (%)
Original signal (241 Hz)	18.05	−0.01	2.11	0.49	—	—
Resampled by window (241 Hz)	18.06	−0.02	2.12	0.48	−0.5	2.0
Resampled by interpolation (241 Hz)	18.06	−0.02	2.01	0.43	4.7	12.2
Resampled (window), filtered (241 Hz)	18.06	−0.02	1.54	0.27	27.0	44.9
Resampled (interpolation), filtered (241 Hz)	18.06	−0.02	1.53	0.25	27.5	49.0
Resampled (window), filtered, subsampled (40 Hz)	18.06	−0.02	1.54	0.27	27.0	44.9
Resampled (interpolation), filtered, subsampled, (40 Hz)	18.06	−0.02	1.53	0.25	27.5	49.0

of the original U signal (it actually is slightly higher than the original signal) and creates a small loss (2%) in the vertical component. As expected, linear interpolation dampens high-frequency fluctuations and results in minor losses for U (4.7%) but more important losses for the V component (12.2%). Note that regardless of the resampling technique, the vertical component of velocity is affected to a greater degree than the streamwise component. This may be ascribed to the fact that a greater proportion of the variance in V is contained in the high frequencies (Heathershaw, 1979). The losses in variance caused by resampling are negligible if compared to those caused through filtering. The differences between the resampling techniques vanish for the U component after filtering and are present, although lessened, for the vertical velocity. Finally, decimation or subsampling does not modify the variance of the signal. It is important to note that the mean velocities are not affected by this data processing. Because filtering is clearly the prevailing cause of any loss in variance, modifying the standard deviation of the Gaussian filter or selecting another type of low-pass filter will affect statistics such as the turbulence intensity (Table 2). It then becomes difficult to make reliable comparisons between data that have not been filtered in an identical manner.

Table 2. Effects of Standard Deviation of Gaussian Filter on Variance (Signal 1)[a]

Type of Gaussian filter	Loss in u variance (%)	Loss in v variance (%)
Half-power at $f_D/6$	27.5	49.0
Half-power at $f_D/4$	22.0	42.2
Half-power at $f_D/2$	15.1	32.2

[a] Loss in variance is computed for signals resampled by interpolation, filtered, and subsampled at 40 Hz.

Spectra

Losses in variance at high frequencies are better visualized by examining the power spectrum of the signals as low-pass filtering creates a rolloff in the inertial range (Fig. 4). The rolloff is obviously the same for all the signals filtered with an equivalent standard deviation, in the situation of a Gaussian filter, or with an identical distribution of weights for other filters (e.g., exponential, moving average). Comparisons of spectral characteristics of different samples therefore are limited to those frequencies which are not affected by the filter. Because a low-pass filter affects a wide range of frequencies lower than

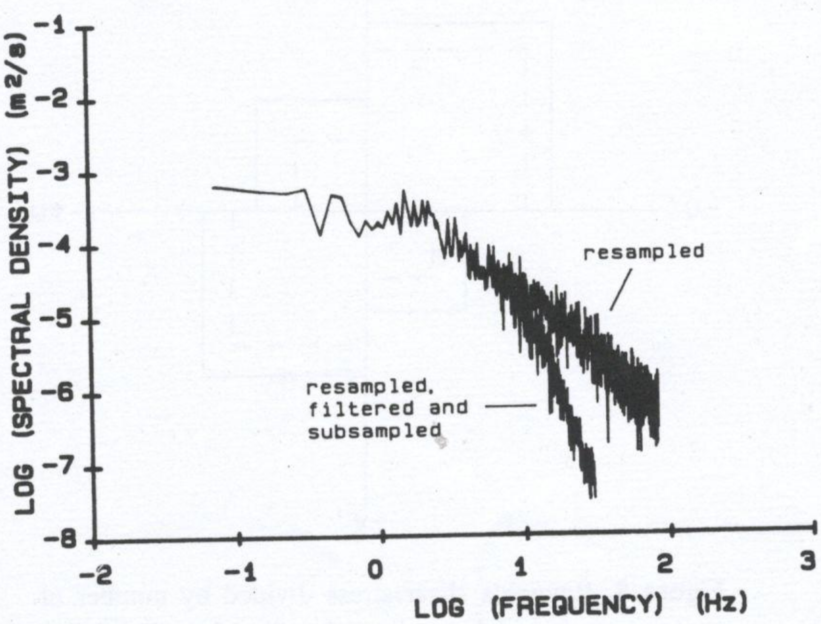

Figure 4. Spectra of Signal 2 resampled (gentle slope) and filtered and subsampled at 40 Hz (sharp roll-off).

the cutoff frequency, a more realistic approach is to limit comparisons of spectral characteristics to a bandwidth between the lowest frequency ($f_{min} = T^{-1}$, where T is the total length of the signal, in sec) and the half-power frequency (f_{50}, equal to $f_D/6$ in this example).

Instantaneous Reynolds Shear Stress

Resampling and filtering will affect high fluctuations and, therefore, high instantaneous Reynolds shear stress, τ, ($\tau = -\rho uv$, where ρ is the water density, u and v are the streamwise and vertical velocity fluctuations, respectively). This is of importance in studies which are concerned with the links between turbulence and sediment transport because high magnitude events, despite their intermittence, play a major role in sediment entrainment and transport (Williams, Thorne, and Heathershaw, 1989). Examination of Signal 1 (Fig. 5) reveals the predominance of quadrant 2 ($u < 0$, $v > 0$, ejections) and quadrant 4 ($u > 0$, $v < 0$, sweeps) events expected in a turbulent boundary layer (Willmarth and Lu, 1972). It is evident that filtering produces a decrease in the average Reynolds shear stress per quadrant (Fig. 5), although the shear stress distribution by quadrant is virtually unchanged. The mean Reynolds shear stress also is affected; for Signal 1, the loss due to resampling, filtering and subsampling is 14.7%.

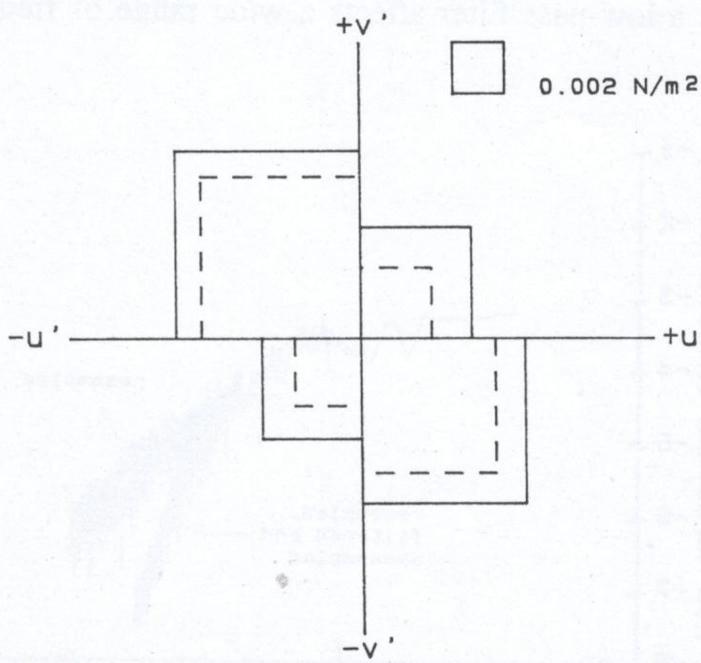

Figure 5. Reynolds shear stress divided by number of occurrences for each quadrant for Signal 1. Solid line represents original signal and dashed line resampled, filtered, and subsampled at 40 Hz signal.

Table 3. Losses in High Instantaneous Reynolds Shear Stress at Different Stages of Data Processing

Signal description	% case > 0.25 $N.m^{-2}$	% case > 0.5 $N.m^{-2}$
Original (241 Hz)	4.58	0.76
Resampled by window 241 Hz	4.46	0.83
Resampled by interpolation 241 Hz	4.02	0.58
Resampled by window, filtered and subsampled at 40 Hz	1.92	0.25
Resampled by interpolation, filtered and subsampled at 40 Hz	1.62	0.25

Table 3 details the influence of resampling and filtering on the relative number of occurrences of high instantaneous Reynolds shear stress. Linear interpolation dampens out the higher frequency fluctuations and produces fewer high instantaneous Reynolds shear stress values than when the original signal is resampled using windowing. Also, as was demonstrated when examining the signal variance, any differences between resampling techniques tend to vanish after filtering, especially for the highest shear stress events (>0.5 $N.m^{-2}$). Finally, the effect of filtering is greatest for the highest shear stresses, where the percentage of cases above 0.5 $N.m^{-2}$ in the original signal is more than three times greater than in the filtered signal. This original: filtered signal ratio is 2.4 and 2.8 at a threshold of 0.25 $N.m^{-2}$ for signals filtered after using the window technique and linear interpolation, respectively.

Scales of Coherent Structures

Autocorrelation functions of U and V and cross-correlation functions of UV are plotted for both signals before and after filtering and subsampling in Figure 6. Signal 1 (Fig. 6A) is characterized by the typical turbulent boundary layer cross-correlation coefficient at lag 0 of approximately −0.4, again illustrating the anisotropic behavior of this velocity signal taken near the bed (Willmarth and Lu, 1972). The cross-correlation coefficient for signal 2 at lag 0 is 0 and reflects the isotropy of the U and V signals above the turbulent boundary layer.

One important statistic derived from autocorrelation functions is the integral time scale which, by Taylor's hypothesis (Lumley and Panofsky, 1964), can be transferred into an integral length scale and yield estimates of the average size of coherent structures. The integral time scale is defined as:

$$I_t = \int_{t=0}^{t=\infty} \rho(t)\, dt \tag{5}$$

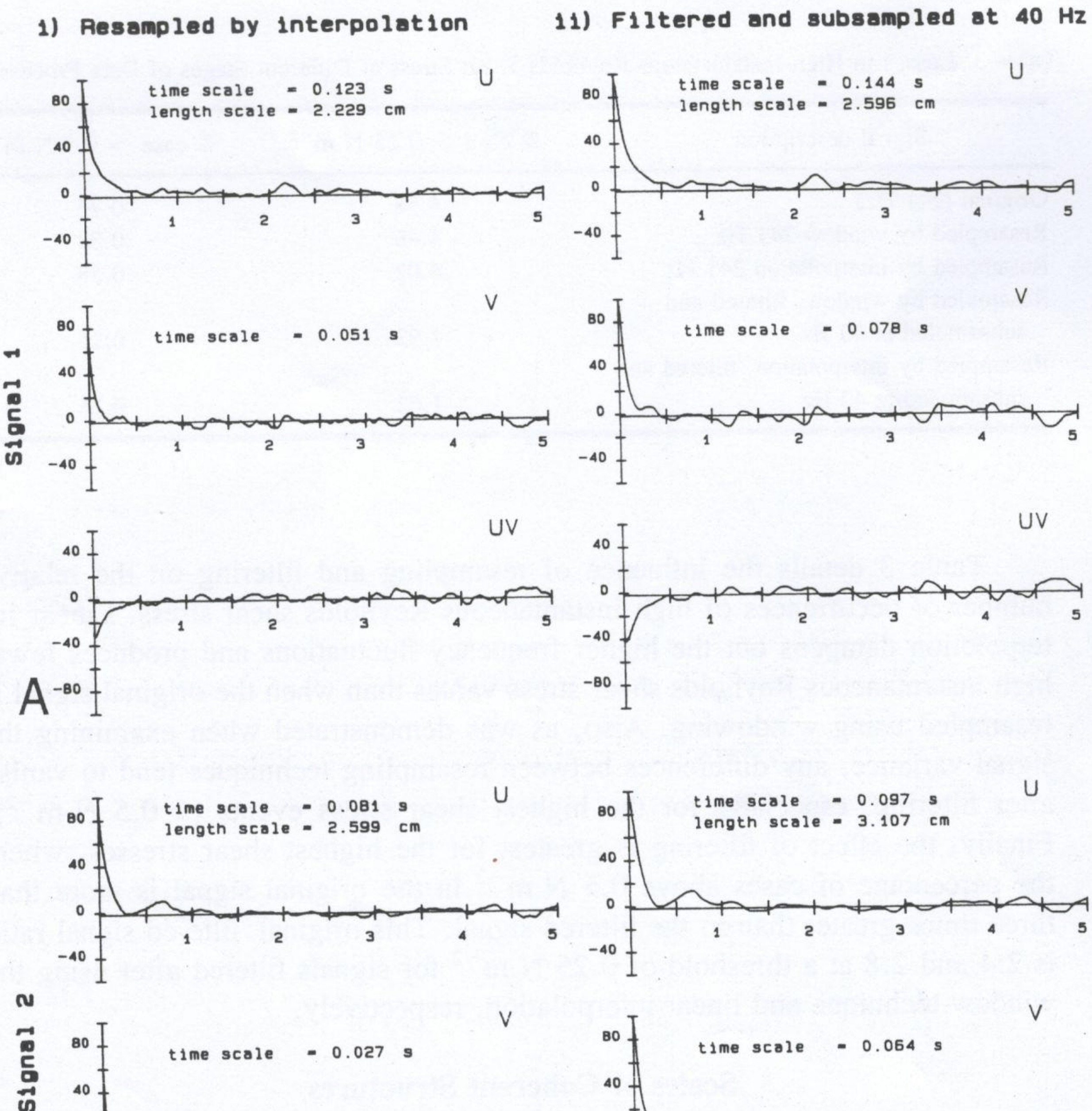

Figure 6. *u*, *v* autocorrelation and uv cross-correlation (in %) as function of lag (in seconds): A, signal 1: (i) resampled by interpolation, (ii) filtered and subsampled at 40 Hz.; B, signal 2, (i) and (ii) as in A.

(Lumley and Panofsky, 1964) where $\rho(t)$ is the autocorrelation function. The integral length scale is simply equal to this value times the mean velocity. Filtering has for a long time been recognized as affecting time-series autocorrelation function (Slutzky-Yule effects; Slutzky, 1927; Yule, 1927). The combined effects of filtering and subsampling (Fig. 6A(ii)) a signal already resampled at 241 Hz (Fig. 6A(i)) show the streamwise integral time scale to increase from 0.123 sec to 0.1445 sec (+18%) whereas the vertical time scale increases from 0.051 sec to 0.078 sec (+53%). It is worthy to note that the streamwise time scale is approximately twice that of the vertical velocity component, illustrating the more coherent behavior of the streamwise signal. A similar increase in time scale is present in signal 2 (Fig. 6B) although differences between the nonfiltered and filtered vertical signals are greater than for signal 1 (137%). This shows that the influence of the filter is greater for the less coherent original signals in the outer flow. As expected, the integral length scale of signal 2 is also greater than that of signal 1 and reflects the measurement point higher in the flow where the eddies are larger (Soulsby, 1980). The cross-correlation is affected by filtering, particularly for signal 1 where the value of the first lag coefficient increases after filtering and becomes closer to the value of −0.4 expected in turbulent boundary layers (Willmarth and Lu, 1972).

DISCUSSION

The preceding analysis has shown that both resampling and filtering affect the original signal in several important ways and that these effects cannot be ignored, even for simple second-order moments (variance) which are statistics used extensively in turbulence studies. If only the moments are required, then the best solution lays in working with the original signal, although this necessarily limits data analysis by excluding statistics that more easily derive from evenly spaced data (e.g., time-series analysis). Biasing problems in the original sample may be solved by residence time weighting.

This study has limited comparison of resampling techniques to linear interpolation and windowing because they represent two extremes: the former method can dampen considerably high magnitude fluctuations whereas the latter leaves them intact. Several methods of interpolation exist (e.g., polynomial interpolation, cubic spline) which are more accurate than linear interpolation for a turbulent velocity signal. However, given the fact that filtering greatly attenuates differences between resampling techniques, the current analysis suggests that use of a more sophisticated interpolation procedure does not warrant the associated complexities and delays in computation. Although the selection of resampling technique is somewhat academic, this study suggests windowing may be more favorable because the measured data remain intact.

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Once it has been established that regularly spaced data are required, the results presented here suggest that it is preferable to set high original average sampling rates in order to subsample all the signals at a common frequency which is determined by the lowest original sampling rate. The common frequency may be dictated by the sampling rates of other measurements where velocity data are allied with other data, such as sediment transport rates or records of changing bed morphology. Whatever common frequency is selected, it is important to adjust properly the standard deviation of the Gaussian filter to the new subsampling frequency in order to avoid aliasing.

In data processing, it becomes dangerous to reach a point where the digital signal no longer gives a true representation of the original continuous signal. If a standard processing scheme is adopted, then it is possible to limit the discrepancies between different sources of data, whether between different LDA measurements data or when comparing LDA data with other measuring instruments. It should not be forgotten that nearly all turbulence measurements are filtered at some stage. For example, ECM signals are filtered routinely with a hardware low-pass RC or Butterworth filter which are a function of the time constant of the instrument. Most ECM data, however, requires only analog low-pass filtering prior to digitization whereas unevenly spaced LDA signals are filtered after digitization.

The use of laser Doppler anemometry is relatively new in earth sciences but is likely to have many new applications in the next few years. This prospect necessitates that some standards for data processing are applied and, perhaps more importantly, that data-processing routines are clearly stated in publications. Otherwise, comparison between results and the more widespread use of an LDA database will remain problematical.

NOTATION

f = frequency, Hz
f_D = sampling frequency, Hz
$f_{\min}$ = lowest frequency, Hz
f_N = Nyquist frequency, Hz
f_{50} = half-power frequency, Hz
I_t = integral time scale, s
R = frequency response
T = total length of a signal, s
U, V = streamwise and vertical instantaneous velocity, m/s
u, v = streamwise and vertical velocity fluctuations, m/s
V_f = freestream velocity, m/s

Y = mean flow depth, m
Y_D = nondimensional height (height of measurement/Y)
$w(t)$ = Gaussian smoothing function
δ = boundary layer thickness, m
ρ = water density, kg/m^3
$\rho(t)$ = autocorrelation function
σ = standard deviation of the normal curve filter, s
τ = instantaneous Reynolds shear stress, N/m^2

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