ABSTRACT

Computing time derivatives is a frequent stage in the processing of biomechanical data. Unfortunately, differentiation amplifies the high frequency noise inherent within the signal hampering the accuracy of signal derivatives. A low-pass Butterworth filter is commonly used to reduce the sampled signal noise prior to differentiation. One hurdle lies in selecting an appropriate filter cut-off frequency which retains the signal of interest while reducing deleterious noise. Most biomechanics data processing approaches utilize the same cut-off frequency for the whole sampled signal, but the frequency components of a signal can vary with time. To accommodate such signals, the Automatic Segment Filtering Procedure (ASFP) is proposed which uses different automatically determined Butterworth filter cut-off frequencies for separate segments of a sampled signal. The Teager-Kaiser Energy Operator of the signal is computed and used to determine segments of the signal with different energy content. The Autocorrelation-Based Procedure (ABP) is used on each of these segments to determine filter cut-off frequencies. This new procedure was evaluated by estimating acceleration values from the test data set of Dowling (1985). The ASFP produced a root mean square error (RMSE) of 16.4 rad.s^{-2} (26.6%) whereas a single ABP determined filter cut-off frequency applied to the whole Dowling (1985) signal, representing the common approach, produced a RMSE of 25.5 rad.s^{-2} (41.4%). As a point of comparison, a Generalized Cross-Validated Quintic Spline, a common non-Butterworth filter, produced a RMSE of 23.6 rad.s^{-2} (38.4%). This new automatic approach is advantageous in biomechanics for preserving high frequency content of non-stationary signals.

Keywords: signal processing, filtering, non-stationary signals, inverse dynamics

INTRODUCTION

Computing time derivatives is a frequent stage in the processing of biomechanical data. Prior to differentiation, high-frequency noise components must be reduced in the sampled signal (Woltring, 1985), which is commonly performed using a low-pass Butterworth filter (e.g., Winter, 2009; Robertson and Dowling, 2003). One hurdle of this approach lies in selecting an appropriate filter cut-off frequency which retains as much of the signal of interest as possible while reducing deleterious noise. The importance of estimating accurate time derivatives for use in inverse dynamics, for example, indicates that this cut-off frequency selection is critical (Mai et al., 2019; Bezodis et al., 2013; Kristianslund et al., 2012).

Procedures have been presented which automatically determine the cut-off frequency for a Butterworth filter (e.g., Winter 2009; Yu et al., 1999, Challis, 1999), which have the advantage that they remove the subjectivity of filter cut-off frequency determination. However, most of these methods have assumed all of a signal of interest lies below one frequency and therefore it is appropriate to use a single filter cut-off frequency for an entire signal. If a certain portion of a signal has higher frequency components than other portions, too low a cut-off frequency can inappropriately attenuate these frequencies. While a higher cut-off frequency might be appropriate for one portion of the signal, for other portions it will fail to appropriately attenuate some of the noise. Non-stationary signals of this nature are common in biomechanics, for example, in gait where leg swing and support portions of a stride have differing frequency components, indeed even the support phase is non-stationary (e.g., Gruber et al., 2017). As such, the ability to filter segments of signals at different cut-off frequencies would permit retention of more of the signal of interest, while simultaneously ridding more of the signal from noise. An adaptive Butterworth filter developed by Erer (2007) aimed to address this by filtering each sample at a different cut-off frequency. Their frequency determination method, however, is sensitive to subjectively selected parameters (see Online Supplementary Material for details). As filter parameters can influence derivative estimates, there is a need for a procedure which can account for and process non-stationary signals objectively and automatically.

The purpose of this study is to present a new procedure which segments a signal based on the signal's time-varying energy, then filters each segment separately with automatically determined cut-off frequencies from the Autocorrelation Based Procedure (ABP; Challis, 1999). This new procedure is evaluated for its ability to produce better derivative estimates from a noisy non-stationary signal compared with commonly adopted procedures.

METHODS

In overview, a new procedure for processing non-stationary signals by dividing them into segments depending on their energy content is presented. The ABP (Challis, 1999) is conducted on each segment independently to produce cut-off frequencies for each segment. This new Automatic Segment Filtering Procedure (ASFP) is evaluated on a test data set and its performance compared with commonly used methods for filtering and differentiating data.

The Procedure

To divide a signal into segments based on its energy content, signal energy was computed as a function of time. The Teager-Kaiser Energy Operator (TKEO; Kaiser, 1990) is an algorithm which calculates the energy of the signal and can be used as a surrogate for more complex time-frequency analysis,

$$TKEO(i) = x_i^2 - x_{i+1}x_{i-1} \quad [1]$$

Where i is the i^{th} sample in a signal x.

This operator was utilized as a means of segmenting a signal. The goal of segmenting was to determine where portions of the signal contain frequency content that differs from the remaining signal. Therefore, TKEO portions which were three absolute deviations (Leys et al., 2013) from the median of the TKEO signal were deemed new segments. Change points were defined as the time index when the TKEO intersected this outlier criterion ($\{t_{cp_1}, \ldots, t_{cp_n}\}$ where n indicates the total number of intersections identified). As the TKEO is sensitive to noise (Kaiser, 1990), an ABP-determined low-pass filter was applied prior to its calculation.

The ABP (Challis, 1999) provided a means of objectively determining Butterworth filter cut-off frequencies for each of the segments ($\{cof_{s_1}, \ldots, cof_{s_m}\}$ for segments $\{s_1, \ldots, s_m\}$ where $m \equiv n + 1$ represents the total number of segments). The full signal, as opposed to only the segment itself, was filtered at each segment-specific cut-off frequency to avoid end-point issues when applying the Butterworth filter (Smith, 1989). Double-differentiation via first-order finite difference equations produced an acceleration signal for each segment-specific cut-off frequency $\{\alpha_{cof_{s_1}}, \ldots, \alpha_{cof_{s_m}}\}$. Reconstruction of the final acceleration signal required the joining of adjacent segments (Figure 1). To do so, overlap sections which were half the length of the shortest segment in the signal were created and straddled each change point. The overlap section's values were calculated by first defining a vector of linearly decreasing weight terms from 1 to 0 along the section's length. The weight term value at a time instance was multiplied by the difference between segment values within the overlap section at this same instance. These weighted differences were then added to the later segment values.

<<<Insert Figure 1 around here.>>>

Evaluation

The data set from Dowling (1985) containing a noisy angular displacement signal and a criterion angular acceleration signal was used as a benchmark. The signal is non-stationary as it contains both an impact and periods of limited movement (Figure 2a). Errors were calculated using the root mean square error (RMSE) between the criterion acceleration signal and the ASFP estimate, as well as the percentage RMSE (%RMSE; Challis, 1999). As an additional comparison, the ASFP was compared to a single filter estimate derived from applying the ABP to the entire signal (Challis, 1999). Finally, as an additional point of comparison, a Generalized Cross-Validated Quintic spline (GCVQS; Woltring, 1986) was used to estimate acceleration values.

RESULTS

<<<Insert Figure 2 around here.>>>

<<<Insert Table 1 around here.>>>

Five automatically determined segments of the Dowling (1985) signal resulted from analysis using the Teager-Kaiser Energy Operator (Figure 2b). Following this segmenting, different filter cut-offs frequencies were used for each segment respectively (Figure 3c). The ASFP produced smaller error results than commonly used filtering techniques (Table 1). The single filter ABP (Challis, 1999), which filtered the signal at 9.6 Hz, produced the largest error at the signal minimum, followed by the GCVQS, whereas the ASFP resulted in the smallest error at this minimum (Table 2). At the signal maximum, this new procedure produced the smallest absolute error, followed by the single filter ABP (Challis, 1999), then the GCVQS (Woltring, 1986; Table 2). Overall, the ASFP produced a better approximation of the criterion acceleration signal compared with other commonly used procedures by automatically segmenting the signal and applying separate filter cut-off frequencies to each respective segment.

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DISCUSSION

Complications inherent to using a single low-pass Butterworth filter on a non-stationary signal have been addressed, and the Automatic Segment Filtering Procedure (ASFP) to process signals of this nature has been presented. The Teager-Kaiser Energy Operator was used to elucidate segments of the signal which contained differing magnitudes of energy. These differing magnitudes indicate the segments have differing signal to noise ratios, thus requiring different filter cut-off frequencies. Segmenting allowed for the use of an automatically determined filter cut-off frequency for each segment. Overall, the procedure demonstrated better second derivative estimates of a noisy, non-stationary signal compared with commonly used approaches.

The first two change points automatically determined here appear to match closely those identified by Dowling (1985), indicating in this region the current procedure is a good approximation of the signal properties which Dowling aimed to treat separately. However, an additional segment was identified in the current procedure that did not match his segment determination. Segmenting in Dowling (1985) was at least partially subjective, with knowledge of the acceleration signal *a priori*. The movement in this region apparently did not appear to warrant segmentation, but the proposed procedure indicates the signal to noise ratio in this area was indeed different from the remainder of the signal. Finally, Dowling's (1985) segmenting was constrained by points where the acceleration estimate was approximately zero, which may hamper the ability to detect all signal segments which require different filtering methods. These results demonstrate the ASFP has sufficient sensitivity to segment a non-stationary signal.

Some considerations must be made when applying the current procedure. As mentioned by Kaiser (1990), the TKEO is itself sensitive to noise. To address this, the TKEO was calculated after the angular displacement signal was low-pass filtered using the frequency cut-off suggested by the ABP computed on this raw signal (9.6 Hz; Challis, 1999). Relatively robust derivative estimates were seen using varying filter cut-off frequencies for the TKEO calculation prior to derivative estimation (e.g., range of filter cut-off frequencies from 3 – 15 Hz resulted in acceleration estimate RMSE values between 15.5 and 19.4 $rad.s^{-2}$). Error results in this study, especially at the signal minimum, are most sensitive to the location of change points in the TKEO. Determining these locations relied on the signal exceeding three absolute deviations from the entire TKEO signal median (Leys et al., 2013). The current signal contains a high frequency impact which lent itself to this outlier detection technique. Some work has used adaptive segmentation thresholds which change along with the signal (e.g., Aragwal and Gotman, 1999). Although not analyzed here, these and other methods may warrant investigation in this setting. Choosing which algorithm to use for segmenting after calculating the TKEO is context specific, but results demonstrated here show that in general, segmenting the signal using the TKEO and applying segment-specific filter cut-off frequencies may be more appropriate than applying one filter cut-off frequency for an entire non-stationary signal that contains impact-like characteristics.

Making use of the proposed procedure for movements like running or jump-landings would see high frequency impact phases filtered at a higher frequency than the remainder of the movement. If the recommendations by Bisseling and Hof (2006) regarding filtering force plate and motion capture data at the same frequency are to be followed, then segmenting the signal in this way would allow greater high-frequency content from a force plate to be retained throughout these impact phases while restricting the influence of noise in lower frequency phases. Movements that inherently contain time-varying frequency content may in fact require a more flexible filtering technique like the ASFP than a single filter cut-off frequency. Improving derivative estimates by using this procedure may assist in determining "true" moments and forces through, for example, inverse dynamics, where acceleration values are of importance.

CONFLICT OF INTEREST STATEMENT

None.

ACKNOWLEDGMENTS

None.

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Table 1 - Error in estimating the criterion angular acceleration signal values determined by three procedures: the Automatic Segment Filtering Procedure (ASFP), the Single Filter Autocorrelation Based Procedure (ABP), and the Single Filter Generalized Cross-Validated Quintic Spline (GCVQS). The errors are expressed as both the root mean square error (RMSE) and the percentage root mean square error (%RMSE), between the criterion angular acceleration values and those estimated by the three procedures.

	RMSE (rad.s^{-2})	%RMSE
ASFP	16.4	26.6
Single Filter (ABP)	25.5	41.4
Single Filter (GCVQS)	23.6	38.4

Table 2 - Error in estimating the criterion signal minimum and maximum angular acceleration values determined by three procedures: the Automatic Segment Filtering Procedure (ASFP), the Single Filter Autocorrelation Based Procedure (ABP), and the Single Filter Generalized Cross-Validated Quintic Spline (GCVQS). The errors are expressed in rad.s^{-2} and as a percentage difference between the criterion angular acceleration values and those estimated by the three procedures.

	Signal Minimum		Signal Maximum	
	Error (rad.s^{-2})	Error (%)	Error (rad.s^{-2})	Error (%)
ASFP	57.7	15.0	-0.8	-0.7%
Single Filter (ABP)	197.8	50.8	1.3	1.1%
Single Filter (GCVQS)	133.2	65.2	-2.3	-1.8%

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Figure 1

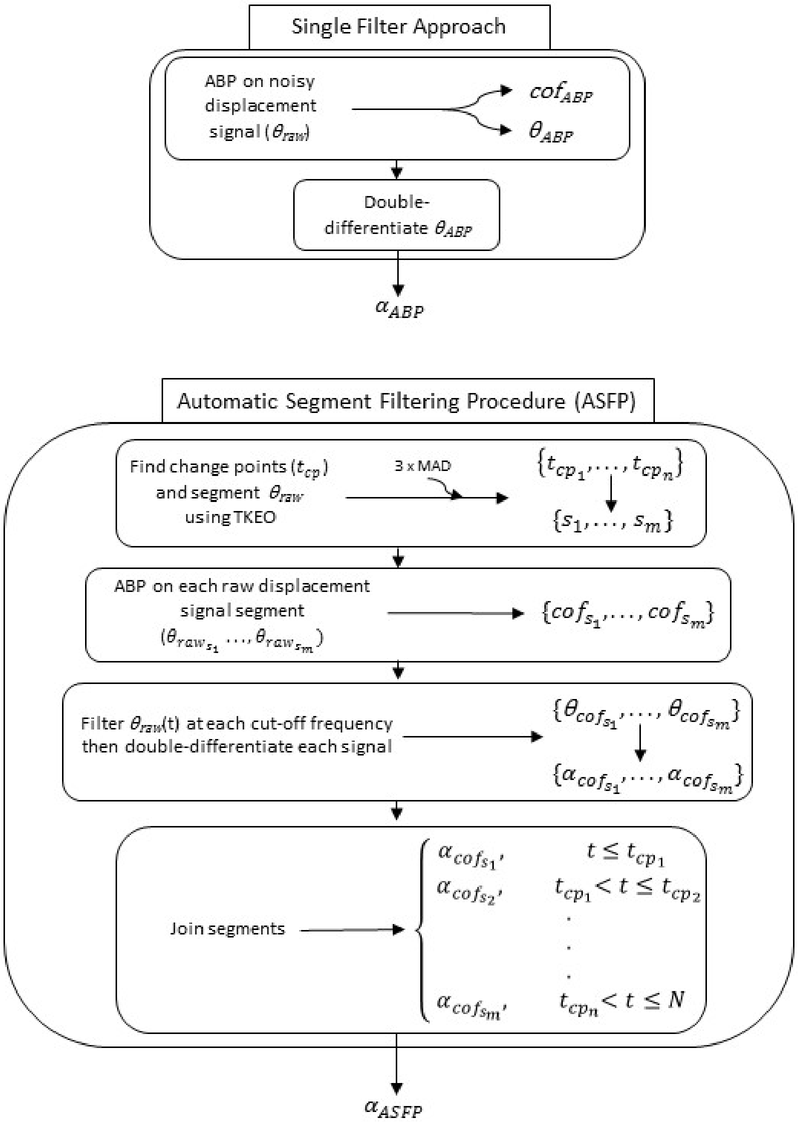
Single Filter Approach
ABP on noisy displacement signal (θ_{raw})
cof_{ABP}
θ_{ABP}
Double-differentiate θ_{ABP}
α_{ABP}
Automatic Segment Filtering Procedure (ASFP)
Find change points (t_{cp}) and segment θ_{raw} using TKEO
3 x MAD
$\{t_{cp_1}, \dots, t_{cp_n}\}$
$\{s_1, \dots, s_m\}$
ABP on each raw displacement signal segment ($\theta_{raw_{s_1}} \dots, \theta_{raw_{s_m}}$)
$\{cof_{s_1}, \dots, cof_{s_m}\}$
Filter θ_{raw}(t) at each cut-off frequency then double-differentiate each signal
$\{\theta_{cof_{s_1}}, \dots, \theta_{cof_{s_m}}\}$
$\{\alpha_{cof_{s_1}}, \dots, \alpha_{cof_{s_m}}\}$
Join segments
$\alpha_{cof_{s_1}}, \quad t \leq t_{cp_1}$
$\alpha_{cof_{s_2}}, \quad t_{cp_1} < t \leq t_{cp_2}$
$\alpha_{cof_{s_m}}, \quad t_{cp_n} < t \leq N$
α_{ASFP}

Figure 2

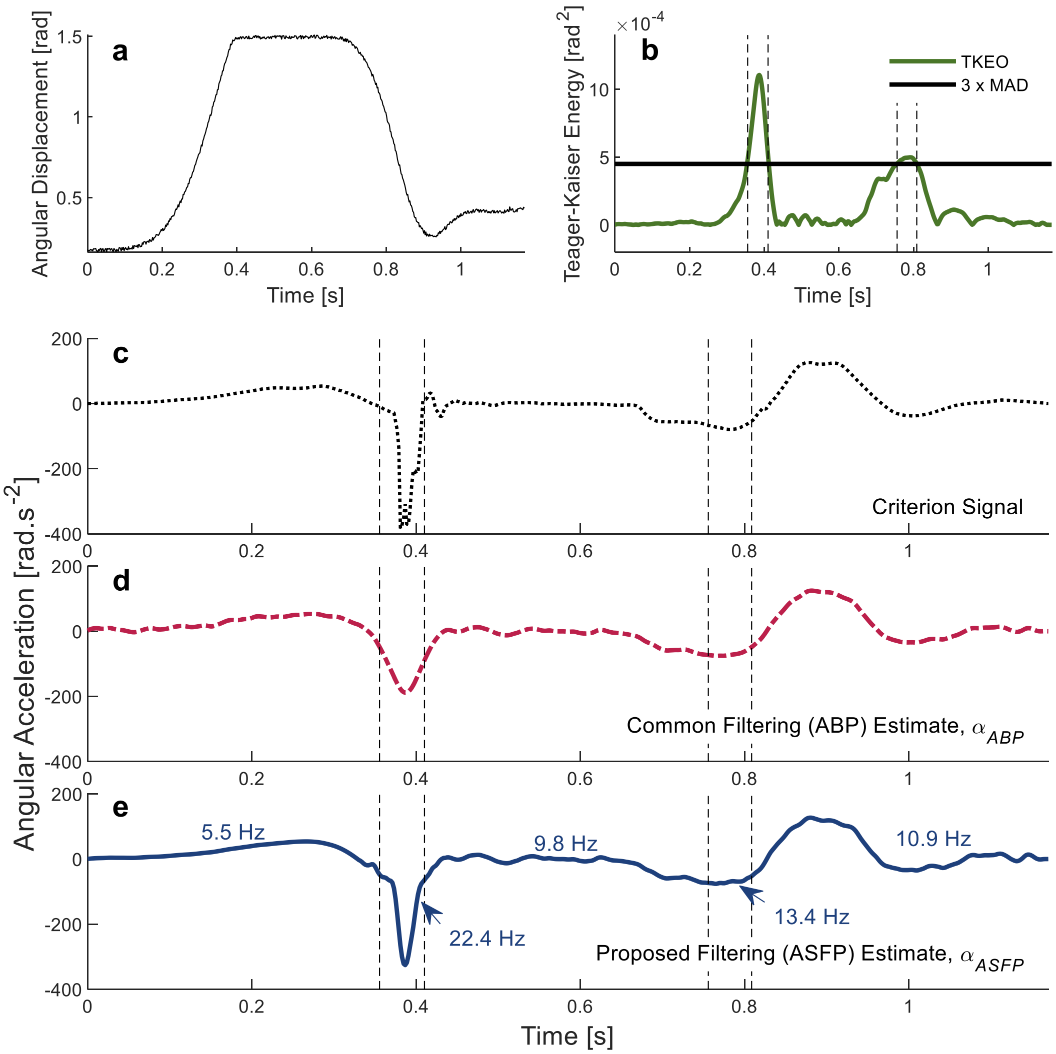
a
Angular Displacement [rad]
Time [s]
b
×10^-4
Teager-Kaiser Energy [rad^2]
TKEO
3 x MAD
Time [s]
c
Criterion Signal
d
Common Filtering (ABP) Estimate, α_{ABP}
e
5.5 Hz
9.8 Hz
10.9 Hz
22.4 Hz
13.4 Hz
Proposed Filtering (ASFP) Estimate, α_{ASFP}
Angular Acceleration [rad.s^-2]
Time [s]

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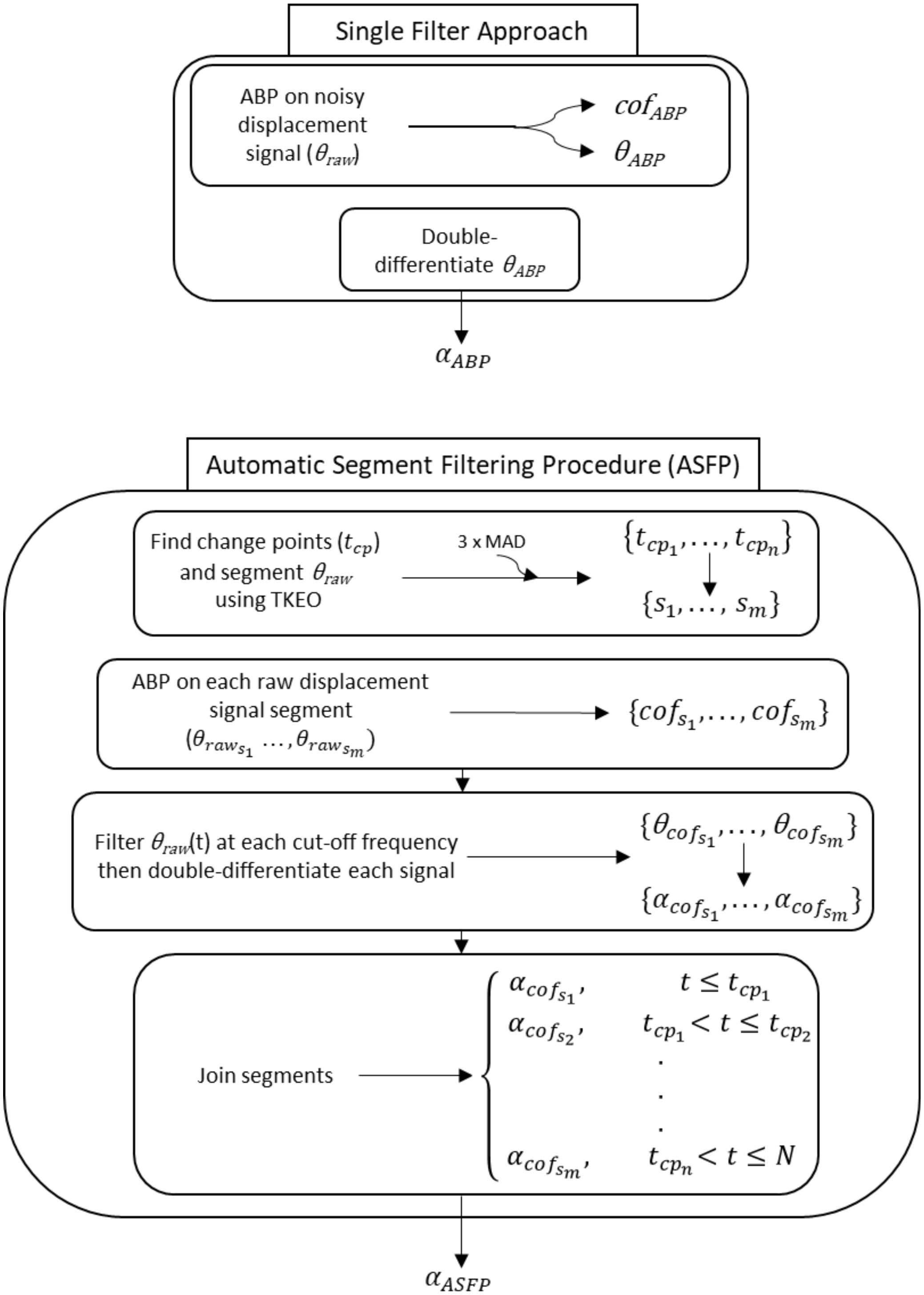
Figure 1- Schematic of a single filter approach and the proposed Automatic Segment Filtering Procedure (ASFP) applied to angular motion signal from Dowling (1985). For the single filter approach, the Autocorrelation-Based Procedure (ABP) determines a single filter cut-off frequency and subsequently uses it to filter the noisy angular displacement signal. The ASFP computes the signal Teager-Kaiser Energy Operator (TKEO) then uses three times its median absolute deviation (MAD) to define time indexes of change points in the signal. The number of change points is defined by *n* and the number of segments used, *m*, is equal to *n* + 1. Values $\{cof_{s_1}, \ldots, cof_{s_m}\}$ represent the filter cut-off frequencies for each respective segment; angular displacement and acceleration values with these as subscripts indicate the signal was originally filtered at this cut-off frequency. *N* represents the last sample in the signal. The first step of the ASFP is depicted graphically in Figure 2b and final results displayed in Figure 2c.

Figure 2- a) Raw angular displacement signal from Dowling (1985). b) Teager-Kaiser Energy Operator (TKEO) of angular displacement signal using the Autocorrelation-Based Procedure (ABP). Vertical lines in panels b through e indicate change points, defined as the intersection of the TKEO with three times its median absolute deviation (3 x MAD). c) Criterion angular acceleration signal published by Dowling (1985). d) Angular acceleration estimate from a single filter approach using the autocorrelation-based procedure (ABP). e) Angular acceleration estimate from the proposed Automatic Segment Filtering Procedure (ASFP) with labels denoting the filter cut-off frequency used for that segment of the raw signal.

Figure 1


Single Filter Approach
ABP on noisy displacement signal (θ_{raw})
cof_{ABP}
θ_{ABP}
Double-differentiate θ_{ABP}
α_{ABP}
Automatic Segment Filtering Procedure (ASFP)
Find change points (t_{cp}) and segment θ_{raw} using TKEO
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$\{t_{cp_1}, \ldots, t_{cp_n}\}$
$\{s_1, \ldots, s_m\}$
ABP on each raw displacement signal segment ($\theta_{raw_{s_1}} \ldots, \theta_{raw_{s_m}}$)
$\{cof_{s_1}, \ldots, cof_{s_m}\}$
Filter θ_{raw}(t) at each cut-off frequency then double-differentiate each signal
$\{\theta_{cof_{s_1}}, \ldots, \theta_{cof_{s_m}}\}$
$\{\alpha_{cof_{s_1}}, \ldots, \alpha_{cof_{s_m}}\}$
Join segments
$\alpha_{cof_{s_1}}, \quad t \leq t_{cp_1}$
$\alpha_{cof_{s_2}}, \quad t_{cp_1} < t \leq t_{cp_2}$
$\alpha_{cof_{s_m}}, \quad t_{cp_n} < t \leq N$
α_{ASFP}

Figure 2

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Figure 2