WAVELET BASED DE-NOISING OF NON-STATIONARY KINEMATIC SIGNALS

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Wavelet Based De-Noising (WDN) is a time-frequency filtering technique that can localise the frequency content of signals. Developments such as translation invariant de-noising and the optimisation of basis function selection have addressed some of the issues associated with WDN reported in the past. The aim of this study was to explore the use of improved WDN techniques for processing non-stationary racket kinematic signals during a badminton smash. WDN was able to better preserve signal features than digital filters and this was especially evident for acceleration. However, 'pseudo-Gibbs' artefacts appeared to be present in some of the signals after double differentiation. Further work should focus on the application of WDN to a wider variety of non-stationary kinematic signals such as the golf swing, baseball batting and tennis strokes.

KEY WORDS: impact, filtering, acceleration, badminton.

INTRODUCTION: Non-stationary kinematic signals, such as those involving impacts, have a frequency content which varies with time. Raw displacement-time data are commonly differentiated in order to calculate velocity and acceleration. The process of differentiation preferentially amplifies higher frequency signals so that low level, high frequency noise in the displacement signals may dominate higher order derivatives (Wood, 1982). Whilst digital filtering techniques, such as the Butterworth filter, can isolate the frequency content of a signal, they cannot distinguish when these components occurred in time. Sharp, high frequency transient components like those caused by impacts are often over-smoothed (Knudson & Bahamonde, 2001; Nunome, Lake, Georgakis, & Stergioulas, 2006).
To avoid such problems polynomial and linear extrapolation techniques have been used to make more accurate estimations of impact parameters (Levanon & Dapena, 1998; Knudson & Bahamonde, 2001); these require precise knowledge of the time of impact and no post impact data can be processed. Time varying filtering techniques such as Wavelet Based De-Noising (WDN) (Wachowiak, Rash, Quesada & Desoky, 2000) and time-frequency filtering in the Wigner distribution (Giakas, Stergioulas, & Vourdas, 2000) have the ability to localise the frequency content of a signal. WDN techniques process the signal at various scales and resolutions, decomposing it into high frequency, low resolution details and low frequency, high resolution approximations. Decomposition is achieved by dilation and translation of a basic mother wavelet and noise is removed via thresholding of the coefficients. WDN has been applied to biomedical signals (Singh & Tiwari, 2006); however, published work utilising WDN in a biomechanical context have mainly dealt with synthesised signals (Ismail & Asfour, 1999; Wachowiak et al., 2000).
Certain issues with WDN techniques have been reported; the presence of 'pseudo-Gibbs' artefacts which present themselves as oscillations around the true signal and the difficulty in choosing a suitable mother wavelet from a large family of candidates (Giakas et al., 2000, Wachowiak et al., 2000; Alonso, Del Castillo & Pintado, 2005). Developments which address these issues, namely translation invariant de-noising (Coifman & Donoho, 1995) and the use of the cross correlation coefficient to optimise mother wavelet selection (Singh & Tiwari, 2006), have yet to be explored in a biomechanics context. Therefore the aim of this study was to explore the use of improved WDN techniques for processing non-stationary kinematic signals, over more commonly used digital filters (Butterworth) with and without pre-filtering extrapolation procedures. Filtering was applied to racket kinematics during an overhead smash in badminton.

METHODS: *Experimental Procedures:* Kinematic data were recorded at 500 fps using a 12 digital-camera motion capture system (Motion Analysis Corporation, Santa, Rosa, CA, USA). Reflective tape was attached to the racket at three locations as shown in Figure 1. One male participant with collegiate level experience (30 y, 94 kg, 1.88 m) volunteered to participate. Written informed consent was obtained and procedures conformed to Sheffield Hallam University's ethics regulations. The shuttlecock was hung from the ceiling at the player's preferred hitting height and the cork of the shuttle was wrapped in reflective tape so that impact could be detected. After warming up, the participant was required to perform 5 maximal effort overhead smash strokes. Marker displacement data were output relative to the global coordinate system (Figure 1).

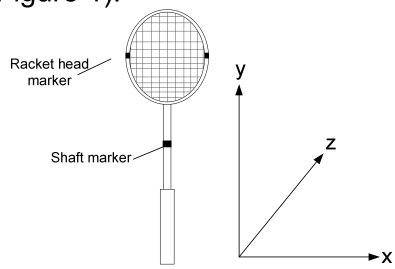

Figure 8: Marker placement and global coordinate system relative to the racket at moment of impact, assuming racket is held vertical at impact (hitting direction=-z).

Data Processing: The raw displacement data were padded to a dyadic length using reflection which also helped to reduce endpoint problems (Smith, 1989). Data were processed using four approaches: 1) the coordinates were smoothed using a second order dual pass Butterworth filter (BWF) with a cutoff frequency determined by residual analysis (Winter, 1990). The optimal cutoff frequency was determined as the frequency at which the second derivative of the residual became less than a threshold value (<0.0006) (Nagano, Komura, Himeno & Fukashiro, 2003). This method was chosen to represent conventional biomechanical filtering procedures (Kwan, Andersen, Cheng, Tang & Rasmussen, 2011). 2) Polynomial Extrapolation (PEXT); a 5th order polynomial was fitted to the last 10 points before impact to estimate the position of impact and extrapolate five frames after impact, this was identical to the procedure used by Knudson & Bahamonde (2001). 3) Linear extrapolation (LEXT); the slope between the second and first frames before impact were used to estimate the position of impact and the five frames after impact (Vint & Hinrichs, 1996). 4) Wavelet Based De-Noising (WDN); The mother wavelet was selected by calculating the cross correlation coefficient of the signal with 17 different mother wavelets; the Symmlet of order 10 was found to be optimal for this data set. Hard thresholding was used in order to maintain the amplitude of spikes in the data (Buckheit & Donoho, 1995). Translation invariant de-noising (Coifman & Donoho, 1995) was employed to reduce 'pseudo-Gibbs' artefacts which have been shown to be problematic (Wachowiak et al., 2000; Giakas et al., 2000). A semi-automatic thresholding technique was implemented similar to methods used by Wachowiak et al. (2000). The threshold (λ) was set to a multiple (α) of the standard deviation (σ) of the wavelet coefficients at each decomposition level i ($\lambda=\alpha_i\sigma_i$). Following empirical experimentation thresholds were determined as follows; for velocity, α_1=6.0, α_2=3.5, α_3=3.0, α_4=1.0, coefficients in the remaining levels were not thresholded. For acceleration thresholds were increased to, α_1=15.0, α_2=10.0, α_3=4.0, α_4=1.0; this was analogous to lowering the cut off frequency for higher order derivatives (Giakas & Baltzopoulos, 1997). Velocity and acceleration were calculated from the processed displacement data using the central difference method. Impact parameters were subject to an analysis of variance followed by the Dunnett test for multiple comparisons between variables. The three Butterworth filter implementations were compared to the WDN condition.

RESULTS AND DISCUSSION: Exemplar velocities and accelerations of the shaft for a single trial are presented in Figure 2. Data are aligned such that impact occurs at t=0.4s. All velocities and accelerations are given in the global coordinate system shown above (Figure 1). The mean velocities and accelerations were similar in magnitude to measurements presented by Kwan et al. (2011).

Table 1: Summary of selected impact parameters for each filtering condition (z direction) (mean ±SD).

	WDN	BWF	PEXT	LEXT
Racket head velocity at impact $m \cdot s^{-1}$	-27 ±3.0	-32 ±2.6	-17 ±50	-44 ±8.6
Shaft velocity at impact $m \cdot s^{-1}$	-24 ±3.1	-23 ±1.6	-27 ±3.9	-29 ±0.9
Racket head acc at impact $m \cdot s^{-2}$	2300 ±690	1900 ±170	5800 ±7400*	210 ±290*
Shaft acc at impact $m \cdot s^{-2}$	1900 ±370	1400 ±140	790 ±1900	43 ±67*

*Significant difference by Dunnet test for comparisons between WDN and other techniques (P<0.05).

Table 2: Summary of max acceleration parameters in WDN and BWF filtering conditions (mean ±SD).

Shaft max acceleration ($m \cdot s^{-2}$)	WDN	BWF
x	540 ±240	370 ±90
y	1600 ±67	1300 ±91*
z	2300 ±280	1400 ±150*

*Significant difference by Dunnet test for comparisons between WDN and BWF (P<0.05).

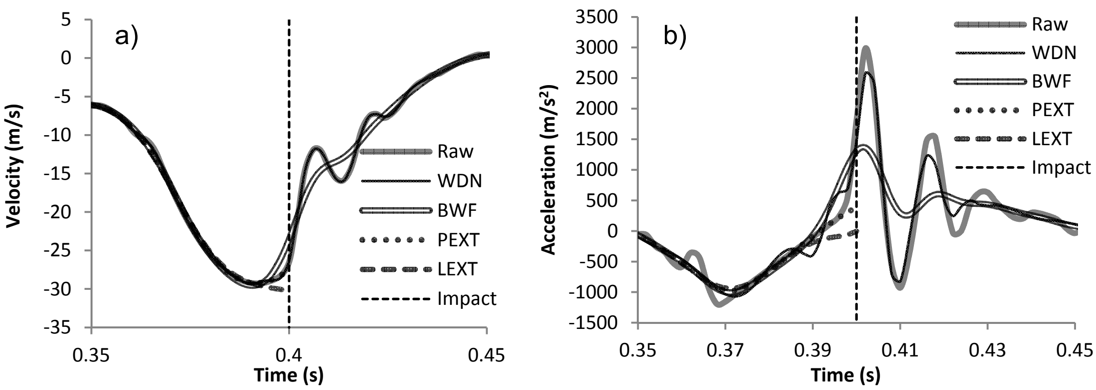

Figure 9: Comparison of a) velocity and b) acceleration of the shaft in the z direction computed for WDN, BWF, PEXT and LEXT conditions.

From Figure 2 is can be seen that WDN preserved the signal features better than BWF which tended to attenuate and widen the higher frequency transients produced by impact, a finding consistent with other studies (Ismail & Asfour, 1999; Wachowiak et al., 2000). This was especially evident for accelerations. For velocity, the PEXT and LEXT conditions produced impact parameters that were statistically similar to the WDN condition (Table 1). The LEXT condition consistently estimated an increasing absolute velocity up to impact which was in line with previous findings related to tennis kinematics (Knudson & Bahamonde, 2001). For some of the data, PEXT produced spurious spikes in velocity around impact that did not resemble signal characteristics; fitting a 5th order polynomial was not always appropriate and the order of the polynomial should be optimised for each signal. For acceleration, impact estimates made by PEXT showed wide variance with SDs of as much as ±7400 $m \cdot s^{-2}$ between trials (Table 1) which were significantly different from WDN. Similarly LEXT was not appropriate for estimating impact acceleration since double differentiation of the constant slope of the extrapolated frames always resulted in low impact accelerations (Table 1). Maximum accelerations estimated by BWF were significantly lower than those estimated by WDN (Table 2). This demonstrates that WDN is better able to preserve the peaks of the signal.

In some acceleration traces such as shown in Figure 2b, characteristics of the 'pseudo-Gibbs' phenomena were visible before impact (Figure 2b, t=0.38s). These manifest as oscillations around the raw signal trace, caused by singularities associated with the exact alignment between features in the signal and features of the mother wavelet (Coifman & Donoho, 1995). Whilst these singularities are localised, unlike Fourier based denoising where Gibbs artefacts are global and of larger amplitude, they could easily be misinterpreted as a kinematic feature. Translation invariant de-noising averages over a range of shifts in order to reduce the effects of this alignment induced phenomena; however the results of this study indicated this problem was not eliminated completely. Alternative time-frequency de-noising methods such as the Wigner function have shown promising results (Giakas et al., 2000; Nunome et al., 2006), however issues with the complexity involved in devising an automatic and systematic implementation procedure and the choice of filter function still exist (Alonso, 2005).

CONCLUSION: WDN is able to better preserve signal features of non-stationary kinematic signals than digital filters. This was especially evident for the double differentiated acceleration signals. Extrapolation procedures were shown to be inappropriate for estimation of acceleration impact parameters. Although improvements have been made to address some of the issues associated with WDN techniques, 'pseudo-Gibbs' artefacts still appeared to be present in some of the signals after double differentiation. Further work should focus on the application of WDN to a wider variety of kinematic signals with impacts such as the golf swing, baseball batting and tennis strokes.

REFERENCES:
Alonso, F. J., Del Castillo, J. M. & Pintado. P. (2005). Application of singular spectrum analysis to the smoothing of raw kinematic signals. *Journal of Biomechanics*, 38, 1085–1092.
Buckheit, J. B. & Donoho, D. L. (1995) *Wavelab and Reproducible Research*. Dept. Statist. Stanford Univ, Stanford, CA. (Online: http://www-stat.stanford.edu/~wavelab)
Coifman, R. R. & Donoho, D. L. (1995). Translation invariant de-noising. In A. Antoniadis & G, Oppenheim (Eds.), *Wavelets and Statistics*, (pp 125–50). New York: Springer-Verlag.
Giakas, G. & Baltzopoulos, V. (1997). Optimal digital filtering requires a different cutoff frequency strategy for the determination of the higher derivatives. *Journal of Biomechanics*, 30, 851-855.
Giakas, G., Stergioulas, L. K. & Vourdas, A. (2000). Time-frequency analysis and filtering of kinematic signals with impacts using the Wigner function: accurate estimation of the second derivative. *Journal of Biomechanics*, 33, 567-574.
Ismail, A. & Asfour, S. (1999). Discrete wavelet transform: A tool in smoothing kinematic data. *Journal of Biomechanics,* 32(3), 317 - 321.
Knudson, D. & Bahamonde, R. (2001). Effect of endpoint conditions on position and velocity near impact in tennis. *Journal of Sport Science*, 19(11), 839-844.
Kwan, M., Andersen, M. S., Cheng, C. L., Tang, W. T., & Rasmussen, J. (2011). Investigation of high speed badminton racket kinematics by motion capture. *Sports Engineering*, 13, 57-63.
Levanon, J. & Dapena, J. (1998). Comparison of the kinematics of the full-instep and pass kicks in soccer. *Medicine and Science in Sports and Excercise*, 30, 917–927.
Nunome, H., Lake, M., Georgakis, A. & Stergioulas, L. K. (2006). Impact phase kinematics of instep kicking in soccer. *Journal of Sports Science*, 24, 11-22.
Nagano, A., Komura, T., Himeno, R. & Fukashiro, S. (2003). Optimal digital filter cutoff frequency of jumping kinematics evaluated through computer simulation. *International Journal of Sport and Health Science*, 1, 196-201.
Singh, B. N. & Tiwari, A. K. (2006). Optimal selection of wavelet basis function applied to ECG signal denoising. *Digital Signal Processing*, 16(3), 175-287.
Smith, G. (1989). Padding point extrapolation techniques for the Butterworth digital filter. *Journal of Biomechanics*, 22, 967- 971.
Vint, P.F. & Hinrichs, R. N. (1996). Endpoint error in smoothing and differentiation of raw kinematic data: An evaluation of four popular methods. *Journal of Biomechanics*, 29, 1637-1642.
Wachowiak, M. P., Rash, G. S., Quesada, P. M. & Desoky, A. H. (2000). Wavelet based noise removal for biomechanical signals: a comparative study. *IEEE Transactions on Biomedical Engineering*, 47(3), 360–368.
Winter, D. A. (1990). *Biomechanics and motor control of human movement*. Wiley, New York.
Wood, G. A. (1982). Data smoothing and differentiation procedures in biomechanics. *Exercise and Sport Sciences Reviews*, 10, 308-362.