SHORT COMMUNICATION

Improved accuracy of biomechanical motion data obtained during impacts using a time-frequency low-pass filter

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Abstract

Biomechanical motion data involving impacts are not adequately represented using conventional low-pass filters (CF). Time-frequency filters (TFF) are a viable alternative, but have been largely overlooked by movement scientists. We modified Georgakis and Subramaniam's (2009) fractional Fourier filter (MFrFF) and demonstrated it performed better than CFs for obtaining lower leg accelerations during football instep kicking. The MFrFF displayed peak marker accelerations comparable to a reference accelerometer during foot-to-ball impact (peak % error = -5.0 ± 11.4%), whereas CFs severely underestimated these peaks (30 - 70% error). During the non-impact phases, the MFrFF performed comparably to CFs using an appropriate (12 - 20Hz) cut-off frequency (RMSE = 37.3 ± 7.6 m/s^2 vs. 42.1 ± 11.4 m/s^2, respectively). Since accuracy of segmental kinematics is fundamental for understanding human movement, the MFrFF should be applied to a range of biomechanical impact scenarios (e.g. locomotion, landing and striking motions) to enhance the efficacy of study in these areas.

Introduction

Accurate quantification of velocities and accelerations using camera-based motion analysis is essential for understanding human movement. To minimise high frequency error from soft tissue artefact and system limitations, marker displacements are low-pass filtered prior to calculation of such parameters (Giakas et al., 2000; Robertson and Dowling, 2003). However, conventional low-pass filters (CFs) (e.g. digital filters) have been criticised for their inability to treat motions involving impacts (Giakas et al., 2000). Since impacts amplify the frequency content of the motion of the impacting body (i.e. causes sudden deceleration) (Georgakis et al., 2002a,b), yet CFs use a constant cut-off frequency for the entire signal time-series (Figure 1), they cannot optimally remove high frequency error from impact and non-impact phases concurrently. This may lead to distortion of variables near to impact and erroneous interpretation of the movement in question (Knudson and Bahamonde, 2001; Nunome et al., 2006). For example, lower limb kinematics have been used to predict injury during foot-to-ground contact in locomotion (Milner et al., 2006; Pohl et al., 2008) and landing motions (Hewett et al., 2005), and distal endpoint kinematics as performance indicators in striking sports (Joyce et al., 2011; Marshall and Elliott, 2000). Use of CFs may ultimately restrict our ability to understand injury risk or performance in these scenarios.

One alternative is to use a filter with a time-varying cut-off frequency, or time-frequency filter (TFF) (Giakas et al., 2000). When the impact induces expansion of the frequency content of a marker, the TFF increases the cut-off value so signal to noise ratios are optimised. TFFs have been used extensively in optics, speech and music processing, and biomedical engineering (Ozaktas et al., 1996), but have been largely ignored by biomechanists. This is despite evidence TFFs outperform CFs during aforementioned activities (e.g. running, Alonso et al., 2005; landing, Georgakis et al., 2002a; and ball kicking, Nunome et al., 2006). Georgakis and Subramaniam's (2009) fractional Fourier filter (FrFF) is one TFF that has been designed for use with marker displacement data, but has not been widely implemented. The FrFF processes marker trajectories in consecutive fractional Fourier domains, and the current study modified the algorithm (MFrFF) (i.e. filter parameter selection) for use during ball kicking motions. Since accurate determination of lower leg kinematics is key for understanding ball kicking performance (Nunome et al., 2006), the aim of this study was therefore to determine if the MFrFF performed better than CF methods for obtaining lower leg accelerations during impact and non-impact phases of football instep kicking.

Methods

Fractional Fourier Filter Parameter Selection and Implementation

Georgakis and Subramaniam (2009) described the design and operation of the FrFF. The algorithm uses a 'triangular' filter boundary which raises the cut-off frequency to retain the time-dependent expansions in frequency content during an impact and determines the appropriate fractional domains with cut-off values based on triangular boundary parameters (Figure 1).

Figure 1 near here

Filter boundary parameters were determined as follows. Non-impact phase cut-off frequencies (X_1), were determined by residual analysis (Winter, 2009). The time of maximum acceleration during impact (t_I) was determined as the instance of peak acceleration (2nd derivative of unfiltered marker displacement) ± 10 ms of the temporal midpoint of impact. Impact width (W) and height (H) were optimised by selecting the filter solution that minimised: a) absolute error (m/s^2) between peak accelerations obtained from MFrFF filtered and unfiltered marker trajectories (i.e. maintaining peak acceleration during impact) and b) mean square error between accelerations from the MFrFF and CF filtered marker trajectory (4th order, dual pass, Butterworth filter, 18 Hz cut-off) ± 10 - 50 ms either side of impact (i.e. reducing high frequency content during pre and post non-impact phases). Iterative implementation of the MFrFF using the '*fminsearch*' optimisation function within Matlab (2017a, Natick, USA) determined the magnitudes of, and ratio between W and H that best satisfied a) and b) for a given marker trajectory. The starting point for calculations was a W to H ratio of 1:11000 (if W = 0.01s, H =

110 Hz) and initial W was manually determined by acceleration of the ball above and below 200 m/s^2 (i.e. ball contact start and end; Nunome et al., 2006). Custom Matlab scripts implemented these routines on individual marker trajectories (i.e. separate X, Y and Z components).

Experiment, Data Collection and Analysis

Football instep kicking induces a considerable impact as the foot contacts the ball (Nunome et al., 2006). If a CF is used to filter 'through' the impact phase, kinematic variables near the time of impact will contain considerable error (Knudson and Bahamonde, 2001). Thus, accelerations from marker trajectories filtered by each MFrFF and five variations of a CF were compared to those from a reference accelerometer (1000 Hz, 14 x 13 x 14 mm, 8 g; ± 1000 G; S3-1000GHA, Biometrics Ltd, Newport, UK). CFs were variations of a 4th order, dual pass, zero lag Butterworth digital filter (chosen as the most commonly used methods in ball kicking literature; Table 1).

Table 1 near here

Following institutional ethical approval and written informed consent, eight semi-professional male footballers (77.3 ± 4.1 kg, 1.78 ± 0.05 m, 25.8 ± 2.9 years) performed ten maximal kicks with a size 5 ball. The accelerometer was attached to the lateral side of the kicking leg 5 cm above the malleolus on a line towards the femoral epicondyle, and tape was wrapped around the leg to ensure it was stationary relative to the shank. Accelerations were filtered on-board by an elliptical filter (cut-off = 312 Hz). The synchronised motion of a reflective marker (12.6 mm) placed on the accelerometer was recorded by a 10-camera, motion analysis system (1000Hz; Vicon T40S, Vicon Motion Systems, Oxford, UK). Trajectories were exported to Visual 3D (V6, Rockville, USA), replicated and filtered in the six filter conditions. Dependent variables were root mean square error (between initiation of final stride to end of follow through; RMSE) and percent peak error during impact (%PE) of resultant accelerations (magnitude of X, Y, Z components) between the accelerometer and motion analysis data (2nd derivative of marker trajectory calculated by finite differences).

One-way repeated measures ANOVAs determined differences in RMSE and %PE between the six filter conditions, compared to accelerometer. If sphericity was violated (Mauchly's = P < 0.05), the Greenhouse-Geisser adjustment was used. Alpha for main effects was Bonferroni adjusted to $\alpha = 0.025$. Bonferroni adjusted contrasts determined pairwise differences between each CF and the MFrFF to further control Type-I error ($\alpha = 0.005$). Effect sizes were calculated as per Cohen (1988). The 95% limits of agreement (LOA; Bland and Altman, 1999) between accelerometer and motion analysis were also calculated for peak values at impact (N = 80 trials). All statistical tests were conducted using SPSS (V23, IBM, New York, USA).

Results

Both RMSE and %PE were different between filter conditions ($p < 0.001$). The MFrFF produced smaller %PE (-5.0 ± 11.4%) compared to the reference accelerometer than each CF ($p < 0.001$; Table 2), with large effect sizes ($d > 0.8$). The BW-250 and BW-DS (228.8 ± 75.4 and 49.1 ± 7.9 m/s^2, respectively) produced larger RMSE values than MFrFF ($p < 0.001$; Table 2), whereas BW-REF (25.4 ± 10.8 m/s^2) produced smaller RMSE values than MFrFF (37.3 ± 7.6 m/s^2; $p < 0.001$). Effect sizes were moderate to large ($d > 0.5$ or $d > 0.8$).

In absolute terms, the MFrFF produced peak accelerations that were 41.6 m/s^2 larger than the accelerometer, but might produce accelerations 133.2 m/s^2 less than (95% CI = 108.3 – 158 m/s^2) or 233.3 m/s^2 greater than (95% CI = 208.2 – 258.2 m/s^2) the accelerometer (Table 2). The BW-12, BW-20, BW-REF and BW-DS displayed 95% LOA that were exclusively lower than the accelerometer (upper limits ratio < 1) and the BW-250 displayed excessively wide LOA. A representative comparison of time-series accelerations obtained from each filter condition is shown in Figure 2.

Table 2 and Figure 2 near here

Discussion

Filter Performance

The MFrFF accurately detected rapid decelerations at the lower leg during foot-to-ball contact, whereas CFs could not. The MFrFF thus retained most high frequency marker content owing to physical sources, while the majority of high frequency noise was attenuated. This supports research that used TFFs to accurately represent landing (Georgakis and Subramaniam, 2009) and ball kicking impact kinematics (Nunome et al., 2006). The BW-250 also retained high-frequency content during impact, but these values were likely indicative of noise that was evident throughout the kick (Figure 2). Conversely, CFs that filtered through impact using a low-cut off frequency severely underestimated marker accelerations during impact. All high frequency content was removed and the sudden deceleration owing to impact was not evident. BW-12 and BW-DS also showed decelerations occurring before impact, which is known to be a result of over filtering (Knudson and Bahamonde, 2001; Nunome et al., 2006). Finally, the BW-REF accurately produced marker accelerations up until ball impact, but was unable to detect changes during and after the impact (Knudson and Bahamonde, 2001). This condition also produced significantly lower RMSE values than the MFrFF, but this was due to the error introduced during and post impact that was included for the MFrFF and missing for the BW-REF.

As well as performing better during impact, the MFrFF also adequately removed high frequency noise from the pre and post impact swing phases. RMSE values were comparable to CFs that used a high sampling rate (1000Hz) and low cut-off frequency (i.e. BW-12 and BW-20) and these methods are known to produce valid accelerations during motions without an impact (Giakas et al., 2000; Robertson and Dowling, 2003). Furthermore, the BW-250 condition was unable to adequately attenuate high-frequency noise during the non-impact phase, and displayed inadequately large RMSE values. Ultimately, the MFrFF maintained good signal to noise ratios during both impact and non-impact phases of the kick, whereas CFs could not.

Practical Implications

The current study modified the FrFF (Georgakis and Subramaniam, 2009) to accurately quantify kinematics during football instep kicking (Nunome et al., 2006). The MFrFF could thus be used to enhance the efficacy of future study involving ball kicking. Furthermore, while this is only one example of MFrFF application, the method has potential to enhance understanding of other human motion involving impacts (e.g. landing and running motions). Since CFs may result in flawed velocities and accelerations near to impact (Knudson and Bahamonde, 2001), researchers should carefully consider the effect that filter choice has on practical interpretation of their data. Interactions occur between the body and the external environment in almost all examples of human motion, and these invariably induce marker displacements that necessitate use of a TFF. It is therefore important TFF methods become widely implemented, and future research should assess the efficacy of TFFs for quantifying kinematic variables during other human movement scenarios.

The MFrFF also addressed some of the barriers that have prevented widespread application of TFFs. First, MFrFF parameter selection was almost entirely automated. The only user input required was to determine the temporal start and end of the impact (Alonso et al., 2005). The chances of manually selecting erroneous parameters and obtaining a non-optimal filter solution were thus minimised. Second, the optimisation process selected filter parameters exclusively from the physical characteristics of marker displacements. While this is not necessarily a novel feature of the FrFF, this study showed the original method can be readily adapted for different impact scenarios. Third, while it is acknowledged the MFrFF required higher sampling rates than commonly used in ball kicking studies (~100 - 500 Hz; Kellis and Katis, 2007), this is typically possible in most well-equipped laboratories. Higher sampling rates are necessary to ensure enough data points are included during the short duration of impact (~10 ms) to allow the FrFF to function correctly. Finally, to date, only the theoretical and computational details of TFFs are available (Georgakis et al., 2002a,b; Georgakis and Subramaniam, 2009). Since these are often complex, it is difficult for researchers to use TFFs without designing their own parameter selection and implementation algorithms. To be useful, future research should present TFFs in formats that are readily integrated with software tools commonly used by motion scientists.

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Conflicts of interest statement

The authors declare no competing, or financial interests.

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References

Alonso, F. J., Castillo, J. M., Pintado, P., 2005. Application of singular spectrum analysis to the smoothing of raw kinematic signals. J. Biomech. 38, 1085-1092.

Ball, K., 2008. Biomechanical considerations of distance kicking in Australian Rules football. Sports Biomech. 7, 10–23.

Bland, J. M., Altman, D. G., 1999. Measuring agreement in method comparison studies. Stat. Methods Med. Res. *8*, 135-160.

Cohen, J., 1988. Statistical power analysis for the behavioral sciences. Academic Press, New York.

Dorge, H. C., Anderson, T. B., Sorensen, H., & Simonsen, E. B., 2002. Biomechanical differences in soccer kicking with the preferred and the non-preferred leg. J. Sports Sci. 20, 293–299.

Georgakis, A., Stergioulas, L. K., Giakas, G., 2002a. Automatic algorithm for filtering kinematic signals with impacts in the Wigner representation. Med Biol Eng Comput. 40, 625-633.

Georgakis, A., Stergioulas, L. K., Giakas, G., 2002b. Wigner filtering with smooth roll-off boundary for differentiation of noisy non-stationary signals. Signal Process. 82, 1411-1415.

Georgakis, A., Subramaniam, S. R., 2009. Estimation of the Second Derivative of Kinematic Impact Signals Using Fractional Fourier Domain Filtering. IEEE T. Signal Proces. 56, 996-1004.

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. J. Biomech. 33, 567-574.

Hewett, T. E., Myer, G. D., Ford, K. R., Heidt, R. S., Jr., Colosimo, A. J., McLean, S. G., . . . Succop, P., 2005. Biomechanical measures of neuromuscular control and valgus loading of the knee predict anterior cruciate ligament injury risk in female athletes: a prospective study. Am. J. Sports Med. 33, 492-501.

Joyce, C., Burnett, A., Ball, K. 2010., Methodological considerations for the 3D measurement of the X-factor and lower trunk movement in golf. Sports Biomech. 9, 206-221.

Kellis, E., & Katis, A. 2007., Biomechanical characteristics and determinants of instep soccer kick. J. Sport. Sci. Med. 6, 154–165.

Knudson, D., Bahamonde, R. 2001., Effect of endpoint conditions on position and velocity near impact in tennis. J. Sports Sci. 19, 839-844.

Marshall, R. N., Elliott, B. C. 2000., Long-axis rotation: the missing link in proximal-to-distal segmental sequencing. J. Sports Sci. 18, 247-254

Milner, C. E., Ferber, R., Pollard, C. D., Hamill, J., Davis, I. S. 2006., Biomechanical factors associated with tibial stress fracture in female runners. Med. Sci. Sports Exerc. 38, 323-328.

Nunome, H., Lake, M., Georgakis, A., Stergioulas, L. K. 2006., Impact phase kinematics of instep kicking in football. J. Sports Sci. 24, 11-22.

Ozaktas, H. M., Kutay, M. A., Mendlovic, D. 1999., Introduction to the Fractional Fourier Transform and Its Applications In: Hawkes, P. (Eds.), Advances in Imaging and Electron Physics. Elsevier, New York, pp. 239-291.

Pohl, M. B., Mullineaux, D. R., Milner, C. E., Hamill, J., Davis, I. S., (2008). Biomechanical predictors of retrospective tibial stress fractures in runners. J. Biomech. 41, 1160-1165.

Robertson, D. G. E., Dowling, J., 2003. Design and responses of Butterworth and critically damped digital filters. J. Electromyogr. Kinesiol. 13, 569-573.

Shinkai, H., Nunome, H., Isokawa, M., & Ikegami, Y., 2009. Ball impact dynamics of instep soccer kicking. Med. Sci. Sports Exerc. 41, 889–897.

Winter, D. A. 2009. Biomechanics and motor control of human movement: John Wiley & Sons, Chichester.

Tables

Table 1. Description of conventional filter conditions. Filter cut-offs of 'filtered through' conditions were chosen to represent studies that have focussed on swing phase (BW-12 and BW-20; e.g. Dorge et al., 2002) or ball impact kinematics (BW-250; e.g. Shinkai et al., 2009). The BW-REF was chosen to show the influence of truncating data before the onset of impact (e.g. Ball, 2008) and BW-DS the effect of down sampling data to a rate comparable to the majority of ball kicking literature (~100 - 400Hz; Kellis and Katis, 2007).

Filter Name	Filter Type	Sample Rate (Hz)	Cut-Off Frequency (Hz)	Impact Phase	Start and End Endpoint Extrapolation
BW-12	4th order, dual pass Butterworth	1000	12	Filtered through	One-hundred frames reflection, removed following filter application
BW-20	4th order, dual pass Butterworth	1000	20	Filtered through	One-hundred frames reflection, removed following filter application
BW-250	4th order, dual pass Butterworth	1000	250	Filtered through	One-hundred frames reflection, removed following filter application
BW-REF	4th order, dual pass Butterworth	1000	20	Truncated one frame before ball contact initiated	One-hundred frames reflection, removed following filter application
BW-DS	4th order, dual pass Butterworth	250	12	Filtered through	Twenty-five frames reflection, removed following filter application

Table 2. Mean ± s.d. percent peak error (%PE) and root mean square error (RMSE) values of each filter condition compared to accelerometer data, pairwise comparisons of each conventional filter technique with the MFrFF, and ratio 95% limits of agreement between peak resultant accelerations obtained at ball impact from each filter condition and the reference accelerometer (N = 80 trials).

		MFrFF	BW-12	BW-20	BW-250	BW-REF	BW-DS
%PE (%)	Mean ± s.d.	**-5.0 ± 11.4**	66.7 ± 7.1	54.1± 9.1	-25.4 ± 18.3	36.1 ± 24.2	64.9 ± 10.7
	p-value		<0.001*	<0.001*	<0.001*	0.001*	<0.001*
	Effect size (*d*)		7.6	5.7	-1.3	2.2	6.5
RMSE (m/s²)	Mean ± s.d.	**37.3 ± 7.6**	45.4 ± 10.8	42.1 ± 11.4	228.8 ± 75.4	25.4 ± 10.8	49.1 ± 7.9
	p - value		0.023	0.152	<0.001*	0.001*	<0.001*
	Effect size (*d*)		0.8	0.4	3.6	-1.3	1.5

	Ratio differences with accelerometer		Ratio 95% limits of agreement with accelerometer			
	Mean	SD	Lower Limit	[95% CI]	Upper Limit	[95% CI]
MFrFF	1.05	0.11	0.84	[0.81-0.87]	1.28	[1.25-1.31]
BW-12	0.33	0.24	0.22	[0.16-0.27]	0.50	[0.45-0.55]
BW-20	0.46	0.15	0.37	[0.33-0.40]	0.63	[0.60-0.67]
BW-250	1.26	0.25	0.75	[0.70-0.81]	1.78	[1.72-1.84]
BW-REF	0.64	0.19	0.42	[0.38-0.46]	0.81	[0.77-0.85]
BW-DS	0.33	0.24	0.21	[0.16-0.27]	0.50	[0.44-0.55]

* denotes significantly different to FrFF condition ($P < 0.005$).

d = 0 - 0.2 trivial effect, 0.2 - 0.5 small effect, 0.5 - 0.8 = medium effect, > 0.8 large effect.

Positive values show peak value from accelerometer was greater than from motion analysis, and vice versa.

Ratio > 1.00 indicates that motion analysis gave a higher acceleration than the accelerometer.

Figure Captions

Figure 1. Example showing constant cut-off frequency (fc) of conventional filter (left) and time-varying fc boundary of the fractional Fourier domain filter (right). *X1* = cut-off of non-impact phase, *W* = width of impact, *H* = height of impact, *ti* = time of impact centre.

Figure 2. Representative trial showing time-series resultant accelerations (magnitude of X, Y and Z components) obtained from accelerometer (red line) and the six filter conditions (black lines) between the events of initiation of final stride (0.6 s) and end of follow through (0.7 s). The respective filter condition is shown above each plot. Vertical dashed lines indicate the start and end of ball impact, respectively.

Figure 1.

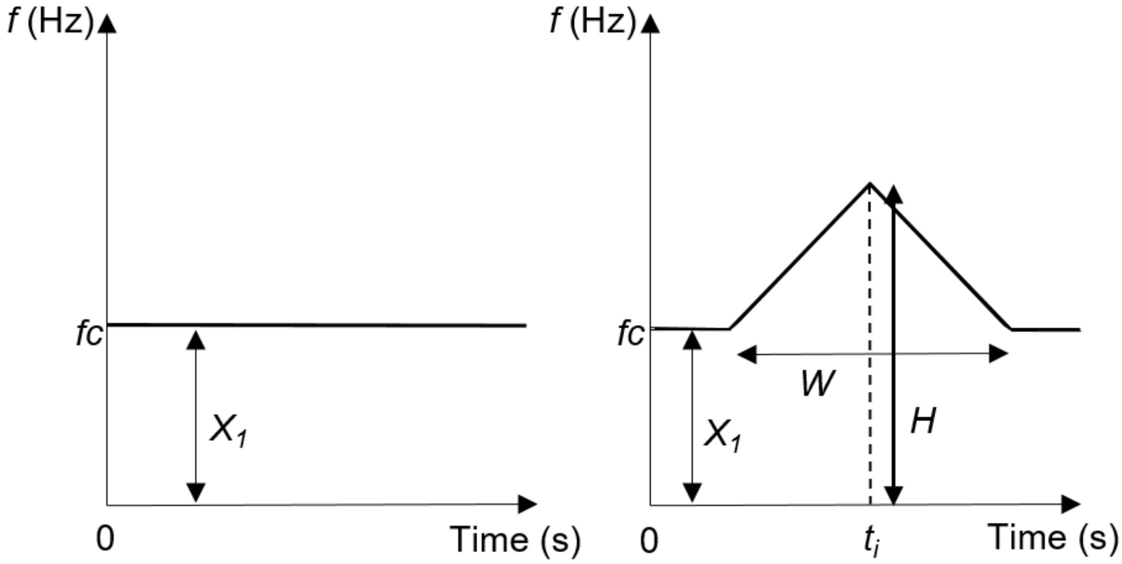
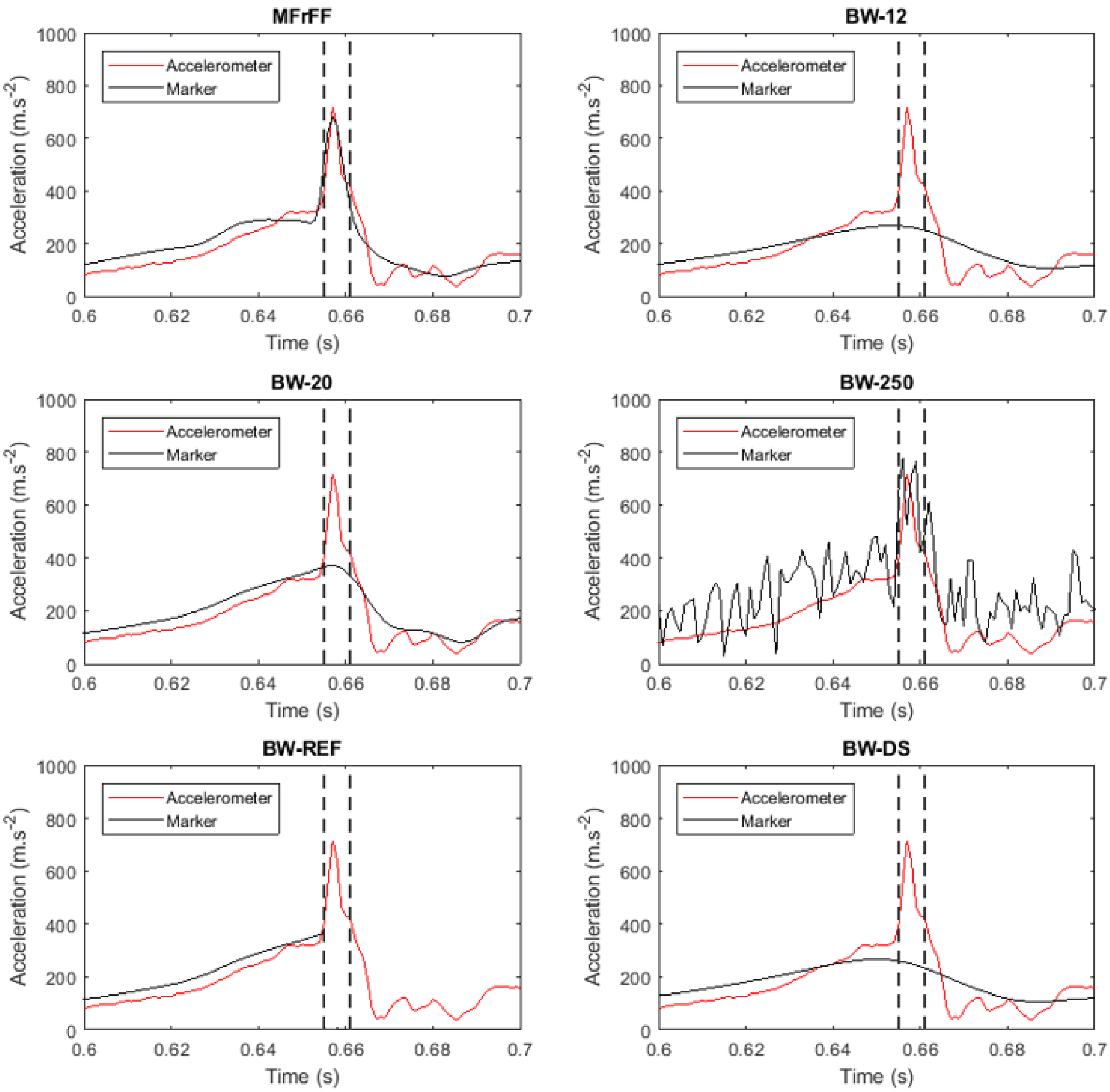


Figure 2.


MFrFF
BW-12
BW-20
BW-250
BW-REF
BW-DS
Accelerometer
Marker
Acceleration (m.s^{-2})
Time (s)
0
200
400
600
800
1000
0.6
0.62
0.64
0.66
0.68
0.7