EVALUATION OF A TIME-FREQUENCY LOW-PASS FILTER METHOD FOR ASSESSING KNEE JOINT MOMENTS AND ACL INJURY RISK

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Time-frequency low-pass filters may enable more precise assessment of knee joint kinetics and help identify athletes at risk of ACL injury. The aim of this study was thus to evaluate use of a fractional Fourier filter (FrFF) for estimating knee joint moments during unanticipated sidestepping. 3D kinematic and GRF data were collected from 11 team sports athletes performing 45° cutting manoeuvres and knee moments were derived in five different low-pass filter conditions. The FrFF produced peak abduction moments similar to 'unmatched' Butterworth low-pass filter conditions (0.7 – 1.2 Nm/Kg) and larger than the 'matched' conditions (0.1 – 0.5 Nm/Kg). This preliminary evidence suggests time-frequency filters can help researchers identify athletes at risk from sustaining ACL injury.

KEYWORDS: inverse dynamics, anterior cruciate ligament, fractional Fourier filter.

INTRODUCTION: Anterior cruciate ligament (ACL) ruptures are devastating knee injuries that incur huge financial and personal cost. They often require expensive surgery and lead to extended absence from participation. Many athletes who sustain injury do not return to pre-injury levels of competition and can suffer from osteoarthritis later in life. Since most injuries occur in non-contact situations (e.g., landing from a jump or change of direction), research has sought to identify biomechanical predictors of injury. For example, peak knee abduction and internal rotation moments observed during sidestepping are purported to classify 'at risk' individuals (Weir, 2021). However, the predictive value of joint kinetics derived from inverse dynamics relies on accurate measurement of segment kinematics and ground reaction forces (GRFs). Whilst it is relatively simple to obtain valid GRFs in a laboratory, questions remain whether conventional low-pass filter methods (e.g., a 4th order Butterworth digital filter) can derive valid segment kinematics (and subsequent joint kinetics) during foot to ground contact (Augustus et al., 2020). Marker data from motion capture tends to be filtered at lower cut-off frequencies than GRFs (e.g., 10 and 50 Hz, respectively), but this can lead to spurious peaks in the computed joint moments. The prevailing convention is thus to filter marker and force data at the same lower cut-off frequency (~10-20 Hz; Bisseling & Hof, 2006) to ensure there is no discrepancy in the frequency content of these inputs. However, this solution is not ideal as it also removes physiologically meaningful information (i.e., higher-frequency segment accelerations) from the signals (Roewer et al., 2012). Given injury often occurs up to 50 - 60 ms after initial ground contact (i.e., weight acceptance; Weir, 2021), attenuation of segment accelerations is problematic as any error will propagate in the inverse dynamics calculations, distort peak knee moments and lead to erroneous classification of injury risk. One alternative is to use a time-frequency filter that raises the cut-off frequency during ground contact to permit retention of faster lower-limb accelerations. Two such methods have shown improvements in assessing higher-order kinematics during the impact phases of running (Davis et al., 2021) and ball kicking (Augustus et al., 2020). If a time-frequency filter can derive more precise estimates of lower-limb kinematics and knee joint kinetics during a lab-based screening test of ACL injury (i.e., unanticipated sidestepping), the capability of researchers and practitioners to successfully: a) identify 'at risk' athletes and b) intervene to reduce injury risk may be enhanced. The principal aim of this study was therefore to evaluate the use of a fractional Fourier, time-frequency low-pass filter (Augustus et al., 2020) for estimating lower-limb kinematics and knee joint kinetics during unanticipated sidestepping compared to conventional filter methods. The secondary aim was to assess whether filter method affects an individual's injury risk classification.

METHODS: Following ethical approval, 11 recreationally active men and women (M = 7, age 26.9 ± 3.7 years, mass 83.5 ± 8.5 kg, height 1.81 ± 0.05 m; F = 4, age 25.3 ± 5.7 years, mass 75.4 ± 10.1 kg, height 1.74 ± 0.04 m) were recruited from local team sports clubs (e.g., football, netball and basketball). After 10 minutes warm up and familiarisation, participants completed three unanticipated sidesteps to 45° on their dominant leg. To perform sidestepping manoeuvres, participants ran towards a Kistler 9287C force platform (approach distance and velocity = 7 - 10 m and 4 - 5 m/s) and timing gates (Smartspeed Pro, Fusion Sports Ltd) placed 2.9 m before the platform triggered a visual stimulus that indicated the required change of direction at random (i.e., left or right). This afforded participants ~400 ms to react to the stimulus and perform the change of direction with the stance foot on the force platform. Trials where the entire stance foot was not on the force platform were discounted and repeated. The GRFs were combined with three-dimensional kinematics (1000 Hz,10 x Vicon T40s, Vicon Ltd) to estimate resultant knee joint moments in Visual3D (v2021.11.3, C-Motion Ltd). Bilateral feet, shanks, thighs and a pelvis segment were defined using inertial parameters from de Leva (1996) and tracked in 6 DOF using triad reflective marker clusters. Anatomical markers (bilateral malleoli and femoral epicondyles) defined segment coordinate systems for the feet and shanks, and joint centres for the ankle and knee, respectively. Pelvis geometry and hip joint centres were defined by anterior and posterior iliac spine markers (i.e., CODA pelvis).
Raw kinematic data were down-sampled to 250 Hz to match that commonly used in the literature and processed in five different low-pass filter conditions. Four conditions used different ‘matched’ and ‘unmatched’ combinations of a 4th order Butterworth digital filter (10-10 Hz, 20-20 Hz, 10-50 Hz and 20-50 Hz), where the first and second values refer to the marker and GRF filter cut-off frequencies, respectively. The fifth condition filtered stance leg foot and shank markers using a fractional Fourier, time-frequency filter (FrFF; Augustus et al., 2020). The FrFF employed a triangular filter boundary whereby a pre-ground contact cut-off frequency of 20Hz linearly increased from initial contact (vertical GRF > 25 N) to a peak cut-off frequency of 60 Hz at the temporal midpoint of weight acceptance, before linearly decreasing back to 20 Hz by the end of weight acceptance (1st trough following peak vertical GRF). To ensure the frequency content of GRFs matched foot and shank segments, these were filtered using the same FrFF algorithm. Markers attached to all other segments (thigh, pelvis and contralateral leg) were filtered using a 4th order Butterworth filter (20 Hz cut-off) as impact induced expansion of frequency content were not evident at these segments. The resultant knee abduction (KAM) and combined non-sagittal moment (NSM; vector magnitude of KAM and transverse rotation moment) were computed for each filter condition using Newton-Euler inverse dynamics. All moments were resolved to the knee joint co-ordinate system and normalised to body mass.
Bonferroni adjusted (α = 0.025) repeated measures ANOVAs analysed differences in peak KAM and NSM during weight acceptance across filter conditions (JASP; v0.14.1). If a significant main effect was identified, planned contrasts examined pairwise differences (N = 4, α = 0.0125) and effect sizes (Cohen’s d) between the FrFF and other filter conditions. To evaluate whether filter condition influenced injury risk classification, a threshold of sample mean + 1.6 SDs was used for each parameter. This threshold has previously been advocated in similar populations (Weir, 2021).

RESULTS: Significant main effects were observed across the five filter conditions for both peak KAM (P < 0.001) and peak NSM (P < 0.001) during weight acceptance (Table 1). The two matched filters displayed significantly smaller peak KAM values than the FrFF with large effect sizes (10-10 Hz = P < 0.001, d = 1.9; 20-20 Hz = P < 0.001, d = 1.5). Peak KAM effect sizes between the FrFF and unmatched 10-50Hz and 20-50Hz filters were medium (d = 0.5) and negligible (d = 0.1), respectively. Each 10-10 Hz (P < 0.001, d = 2.3), 20-20 Hz (P < 0.001, d = 1.9) and 20-50 Hz (P = 0.008, d = 1.0) displayed smaller peak NSM values than the FrFF with large effect sizes. One participant (P6) was identified as ‘at risk’ by both KAM and NSM in all filter conditions except 10-10 Hz. Another participant (P1) was identified by KAM and NSM as ‘at risk’ in the FrFF condition only (Table 1). Representative time-series joint moments and lower-limb accelerations from a single trial are shown in Figure 1.

Table 1. Individual participant and sample mean ± SD peak knee abduction (KAM) and non-sagittal (NSM) moments during weight acceptance in each filter condition. * indicates a pairwise difference to the FrFF condition. ** indicates the individual exceeded the risk threshold for that variable and filter condition (i.e., > M + SD*1.6). (F) = female athlete.

All Units =	FrFF		10-10 Hz		10-50 Hz		20-20 Hz		20-50 Hz	
Nm/Kg	KAM	NSM	KAM	NSM	KAM	NSM	KAM	NSM	KAM	NSM
P1 (F)	1.66**	1.74**	0.51	0.60	1.22	1.44	0.86	0.93	1.09	1.19
P2	0.11	0.67	-0.30	0.38	0.04	0.60	-0.15	0.49	0.80	0.52
P3 (F)	0.32	1.20	0.05	0.49	0.30	0.57	0.22	0.57	0.39	0.58
P4	1.06	1.28	-0.01	0.41	0.76	1.34	0.65	1.03	0.75	1.16
P5	0.79	1.19	0.01	0.41	0.69	0.95	0.32	0.62	0.71	0.95
P6 (F)	1.72**	1.80**	0.61	0.76	1.61**	1.65**	1.10**	1.41**	1.64**	1.66**
P7 (F)	0.90	1.10	0.42	0.43	0.83	0.99	0.46	0.62	0.71	0.91
P8	0.82	0.96	0.05	0.21	1.06	1.20	0.28	0.44	0.99	1.08
P9	0.70	1.19	0.52	0.71	0.90	1.10	0.67	0.93	0.90	1.04
P10	0.85	1.04	-0.05	0.50	0.77	0.89	0.26	0.68	0.52	0.82
P11	0.22	0.88	-0.15	0.71	0.07	0.83	0.25	0.83	0.30	0.85
M	0.83	1.19	0.15*	0.51*	0.75	1.05	0.45*	0.78*	0.80	0.98*
SD	0.52	0.34	0.31	0.17	0.48	0.34	0.35	0.28	0.37	0.31
M + SD*1.6	1.66	1.72	0.64	0.78	1.51	1.59	1.00	1.23	1.39	1.48

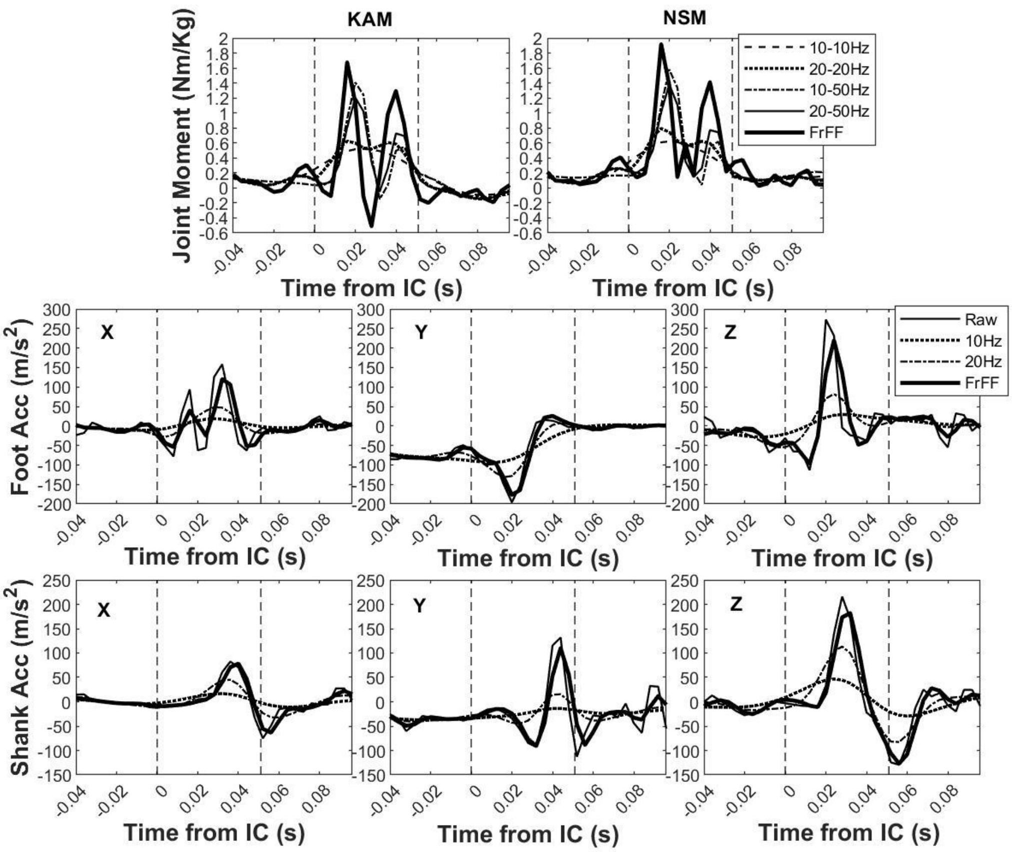

Figure 1. Representative knee abduction (KAM) and non-sagittal (NSM) moments (top row), triaxial foot CoM accelerations (middle row) and triaxial shank CoM accelerations (bottom row) during initial ground contact (IC) in each filter condition. Vertical dashed lines indicate the start and end of weight acceptance. X = medio-lateral, Y = anterior-posterior and Z = vertical.

DISCUSSION: The FrFF produced peak KAM and NSM values larger than those in the conventional 'matched' filters (10-10 Hz and 20-20 Hz) and similar to those in the 'unmatched' conditions (10-50 Hz and 20-50 Hz). It is well known that lower and matched cut-off frequencies produce smaller and smoother peak knee moments (Rower et al, 2012) and unmatched filters produce larger impact peaks that originate from discrepancies in kinematic and GRF frequency content (Bisseling & Hof, 2006). In contrast, the FrFF used an adaptive cut-off frequency, so the larger peak moments observed in this condition were likely due to retention of faster foot and shank accelerations following ground contact. Indeed, the FrFF acceleration data were more representative of the Raw values and this higher-frequency content was also evident in the joint moments (Figure 1). While this indicates the FrFF derived moments would be more accurate estimates of the 'real' knee moments experienced during sidestepping, it is pertinent to comment on the sources of those accelerations. Ideally, motion and GRF data should be filtered at the highest frequency that removes noise yet leaves the physiologic signal intact. The impact peak cut off frequency (60 Hz) was thus chosen to capture the entire range of lower-limb accelerations induced by ground contact (Augustus et al., 2020), but it is plausible some noisy oscillations (e.g., soft tissue artefact) were retained. It is therefore difficult to imply that the FrFF produced knee moments that were closer to true values than the conventional filters. This also explains why Bisseling & Hof (2006) originally advocated using matched cut-off frequencies of ~20 Hz to derive joint moments during dynamic sporting activity. Unfortunately, it is often overlooked that they also advised low and matched cut-off frequencies should not be used if impact peak moments are of interest. While such methods are suited to situations where general patterns of neuromuscular function are of interest (e.g., net joint moments during a walking gait cycle), situations that necessitate closer inspection of impact accelerations in relation to joint kinetics (e.g., using peak KAM and NSM values to assess ACL injury risk) might benefit from use of the FrFF. Importantly, however, the highlighted variation in peak KAM and NSM values across filter conditions did not drastically alter risk classification (Table 1). One participant (P6) was identified as 'at risk' in all but the 10-10 Hz conditions and another (P1) was only identified as at risk by the FrFF. This suggested all but the most aggressive filter condition were sensitive enough to identify athletes displaying elevated knee moments indicative of injury risk. However, given the small sample size, it is difficult to determine whether the 'at risk' classification given to P1 in the FrFF condition was indicative of enhanced sensitivity to deficient biomechanics, or a false positive finding. While this preliminary evidence suggests time-frequency filters can help researchers and practitioners identify athletes at risk from sustaining ACL injury, future research must assess such methods against criterion measures of knee joint loading to better understand their performance compared to conventional filer methods. Their performance should also be evaluated in varied populations (e.g., younger athletes) and in different screening tests (e.g., drop vertical jumping). Ultimately, this study has highlighted the importance of low-pass filter selection when conducting inverse dynamics to assess ACL injury risk. Sports biomechanists should carefully consider a) the influence different filter parameters have on interpretation of their data (i.e., type, cut-off frequencies and matched vs unmatched combinations) and b) whether chosen filter methods are appropriate for the context and/ or variables under investigation.

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