COMPARISON OF DISCRETE (0D) AND CONTINUOUS (1D) ANALYSIS OF SIDESTEP CUTTING KINEMATICS AND KINETICS

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Although both discrete (0D) and continuous (1D) analysis are used, the differences in results between both analyses in repeated measures designs are unclear. Therefore, the purpose of this study was to explore if discrete and continuous analysis on the same dataset lead to different conclusions. Data of an intervention study regarding sidestep cutting with two groups and three sessions of measurements were used. Analyses of mean and peak values (0D) and timeseries (1D) revealed contradictory results for some variables. More interestingly, the direction of the results was different sometimes. This substantiates the impact that an analysis method can have on data interpretation and warrants caution in drawing conclusions. Researchers are encouraged to ensure that their analysis method is appropriate to answer their research question and a priori hypothesis.

KEYWORDS: spm1d, movement execution, time series, statistics, lower body, female athlete

INTRODUCTION: Traditionally, discrete point analysis is used to analyze kinetic and kinematic data, reducing continuous data to a single point (i.e., mean or peak value). This summary-metric is not strictly necessary as statistical hypothesis testing could be conducted in a continuous manner, directly on the original (registered) curves using statistical parameter Mapping (Pataky, 2012). This enables a more comprehensive approach by assessing entire movement curves instead of solely focusing on the mean or peak values of specific movements. Through the application of spm1D, researchers can analyze simple and complex movements of the lower extremity, identifying subtle patterns that may not be evident through traditional discrete point analysis. By expanding the window of analysis (e.g., entire stand phase), the spatiotemporal biomechanical context is preserved and more information regarding the variable of interest is retained. This allows for the extraction of information regarding safe movement strategies which is essential to evaluate prevention programs. Moreover, it provides the opportunity to compare variables over the same time window (e.g., the first 40ms) with each other instead of the peak knee flexion angle and abduction angle which possibly occurred at different points in time. Nevertheless, spm1D is still underutilized in evaluation of (anterior cruciate ligament (ACL) injury) prevention programs. Pataky et al. highlighted differences between 0D and 1D confidence intervals (Pataky et al., 2015) and probability of false positives in 0D analyses of 1D data (Pataky et al., 2016). However, the differences in results between discrete and continuous analyses on a repeated measures design are still not clear. Therefore, the purpose of this study was to explore if discrete (0D) and continuous (1D) analysis of kinematic and kinetic data leads to different conclusions and thus implications. A dataset of a four week intervention program aiming to improve sidestep cutting execution was used. We hypothesized that there would be differences in results between the two analyses as the discrete analysis uses summary-metrics which loses spatiotemporal information.

METHODS: Twenty healthy talented female soccer players (mean age 14.9 ± 1.0 y, 168.2 ± 5.1 cm, mass 56.1 ± 7.3 kg) participated. The first cohort formed the video intervention (VIDEO) group (n=10), the second cohort formed the control (CTRL) group (n=10). The players trained 4 times a week (75 min per training) and played one match per week. For inclusion, players had to be between 12 and 18 years old and had to be part of the Regional Talent Center Soccer North (Groningen, The Netherlands). No power analysis was performed prior to this study, as there is no software available yet to perform 1D sample size estimation for two-way analyses. Therefore, we based our sample size on comparable previous studies (Celebrini et al., 2014; Dos'Santos et al., 2019). Ethical approval was obtained from the University Medical Center

Groningen (ID number: METc 2018.249). Informed written consent of subjects and/or legal guardians were obtained prior to inclusion.
Since data was used from a previous article, the procedures for the measurements are described in detail there (Nijmeijer et al., in press). The current study focuses on unanticipated sidestep cutting. In contrast to the CTRL group, the VIDEO group received expert video instruction during the training sessions. The experts showed a preferable movement pattern with alignment of hip and knee in the cutting direction. Moreover, the knee flexion angle is highly increased from initial contact to weight acceptance and the body is aligned with the vertical ground reaction force (vGRF) vector. Primary outcome measures were lower-body kinematics and kinetics and vGRF. As literature has not reached consensus about the optimal cut off frequency, i.e., some proposed matching frequencies (Kristianslund et al., 2012) whereas others used different frequencies for marker and force data (e.g., Weir et al., 2019), a residual analysis (Winter, 2009) was used to determine the optimal cut off frequency with the python package *optcutfreq* (Duarte, 2021). After visual inspection, the mean optimal cut off frequency was chosen, which was 10 and 125 Hz for marker and force data, respectively.
A customized python script (Python Software Foundation, Delaware, USA, version 3.11) was used to pre-process the data and perform the statistical analyses the 0D and 1D data. Analysis on the 0D data was performed twice; on the mean and peak absolute value of the entire stand phase ($\alpha<.05$). 1D data includes the entire stand phase (vGRF > 20N (Dos'Santos et al., 2021). Non-linear registration was used for the 1D analysis, as proposed by Pataky et al. (2022). As multiple peer models were used (with matched anthropometrics to subject), delta waveforms were calculated for each trial by subtracting model waveform from subject waveform. As the normality was violated, non-parametric procedures were performed (Pataky et al., 2015) for the 1D data. As we focus on amplitude effects, the significance level was set a priori to <.025 (Pataky et al., 2022). The open-source software package spm1D 0.4 (https://spm1d.org/) was used to perform the 1D analysis with Statistical Parametric Mapping (SPM). Two-way ANOVA analysis with repeated-measures on one factor (time) was performed to analyse group (CTRL and VIDEO) and time (baseline, immediate-post and retention) effects. Non-parametric paired *t*-tests with Bonferroni corrections were used as post-hoc tests if significant differences within subjects were found for either 0D or 1D analysis.

RESULTS: No significant differences were found in any analysis for the hip flexion angle and moment, knee flexion angle and moment, and vGRF. Table 1 shows main effect of group or time differences for both the 0D and 1D analysis. The 0D analyses show significant results for three variables ($p<.05$), whereas the 1D analysis shows significant results for five variables ($p<.025$). Differences between the analyses were found in, for example, the ankle plantar flexion angle. Whereas the 0D analysis showed greater values for the control group (peak: $p=.010$, mean: $p=.008$), the 1D analysis showed greater values for the VIDEO group ($p=.002$). Moreover, the 0D analysis showed a main effect of group for the hip abduction angle ($p<.001$), while the 1D analysis found a main effect of time ($p=.029$). Figure 1 shows the mean and standard deviation cloud of the ankle plantar flexion angle.

DISCUSSION: The purpose of this study was to explore if discrete (0D) and continuous (1D) analysis of kinematic and kinetic data leads to different conclusions and thus implications . A dataset of a four week intervention program aiming to improve sidestep cutting execution was used. The 0D analyses found significant differences for three variables, whereas the 1D analysis did for five variables. Even more interesting, the direction of the results differed sometimes between the analyses. For example, whereas the 0D analysis of the ankle plantar flexion angle showed greater values in the CTRL group, the 1D analysis revealed a significant cluster with greater angles for the VIDEO compared to the CTRL group. The differences may be explained by the fact that 0D analysis uses summary-metrics. In other words, it compares peak values which could have been observed at different moments in time. For the ankle plantar flexion angle, the mean peak value of the CTRL group occurred at 53%, whereas it was at 56% for the VIDEO group. Although these points in time are not that far away from each other, it may explain why no significant differences around 50-60% occurred in the 1D analysis.

In contrast, the 1D analysis, preserving the spatiotemporal context, revealed differences between groups at the end of the stance phase. Moreover, the 1D analysis does not specifically look at peak values, it focuses on the difference at each time point and may therefore come up with other results. In conclusion, the differences seen in the outcomes of the analyses may result in different advice to athletes or coaches to change movement patterns.
Reducing 1D data to single point data goes hand in hand with losing information about the curve of the signal. The results are often joint-specific snapshots during a short time window (or even 1 frame) (Bolt et al., 2021). For example, information about the timing of peak values could be lost when using discrete point analysis. This spatiotemporal biomechanical context is preserved when using the original (registered) data and applying continuous analysis.

Table 1. P-values of two-way ANOVA with repeated measures on time and post-hoc analysis with peak values, mean values, and time series

	Main effect time			Main effect group		
	Peak	Mean	Time series*	Peak	Mean	Time series*
Hip abduction angle (°)			<.001 (0-100%) imm < ret: .003 (1.7-22.3%)	.029 VIDEO > CTRL		
Ankle plantarflexion angle (°)				.010 CTRL **>** VIDEO	.008 CTRL**>** VIDEO	.002 (82.9-100%) VIDEO **>** CTRL
Hip abduction moment (Nm/kg)	. 019 <u>Post hoc:</u> Imm > base (.014)	.017 <u>Post hoc:</u> Imm > base (.014)	.013 (9.3-14.0%) .018 (17.6-20.4%) <.001 (34.6-94.0%) <u>Post hoc:</u> base vs imm: .005 (11.5-13.8%) & <.001 (33.4-87.7%)			
Knee abduction moment (Nm/kg)			.004 (96.5-100%) <u>Post hoc</u>: base > imm: .005 (97.9-100%) ret > imm: .003 (96.3-100%)			
Ankle plantar flexion moment (Nm/kg)			.005 (7.3-28.9%) .015 (78.4-85.5%)			

*significant clusters are depicted as % of stance phase, base: baseline test; imm: immediate-post test; ret: retention test; VIDEO: video intervention group; CTRL: control group, > indicates direction of difference

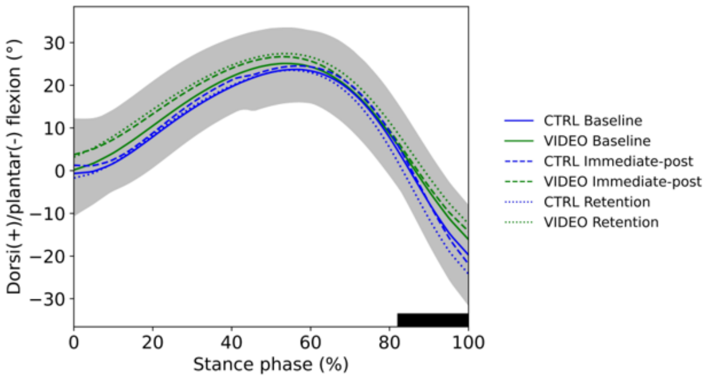

Figure 1: Mean and standard deviation cloud of ankle flexion angle (for readability we just plotted maximum standard deviation (regardless of group and test))

The results substantiate the impact an analysis method can have on interpretation of the data (Pataky et al., 2016). Especially in injury prevention programs, a reductionist approach (i.e., single point data) often reduces the data and discards important information regarding injury risk, i.e., timing of peak value (Bolt et al., 2021). A more holistic approach, such as 1D analysis, provides more profound information which helps our understanding of ACL injury risk mechanisms. Moreover, it allows to get a more comprehensive understanding of the contribution of several variables together which eventually may place an individual at risk (i.e., small knee flexion angles combined with great knee abduction moments during the first 40ms). The choice of 0D or 1D analysis should be made based on the a priori hypothesis. If, prior to conducting an experiment, one explicitly identifies a particular 0D metric as the sole metric of interest, then the research question is inherently 0D and the 0D result is correct (i.e., knee flexion at impact). On the contrary, when the a priori hypothesis is related to 1D metrics (i.e., GRF or muscle forces during stance) and key events in the data are expected (i.e., heel contact and toe-off), 1D analysis is preferred (Pataky et al., 2015).

CONCLUSION: The current study applied 0D and 1D analysis on the same dataset and showed that the choice of analysis method influenced the results and therewith interpretation of the intervention. Researchers are encouraged to ensure that their analysis method is appropriate to their research question and a priori hypothesis.

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