

# CREATION OF THEORETICAL DATA SETS TO EXAMINE MOVEMENT VARIABILITY USING MODELLING

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**INTRODUCTION:** Recently, a large amount of research has been focused on the effect of movement variability on human performance in sport. It is now generally accepted that specific amounts of variability are essential to attain a high level of performance (Davids *et al.*, 2003). When studying the effect of movement variability on outcome performance, the usual method involves collecting numerous data sets from an individual and, assuming that these data sets will all be different (i.e. contain variability), attempt to connect the amount of variability to the change in outcome or performance measure using a number of statistical techniques. The aim of this study is to remove the requirement to collect a large amount of data which, by chance, may contain the level of variability required and shorten the data collection phase significantly by using the proposed process to create theoretical data sets containing alterable variability content while still exhibiting major characteristics of the actual data. When these theoretical data sets are used in conjunction with a full-body 3D computer model operating inverse and forward dynamics simulations a change in outcome or performance measure can be predicted. The advantages this process offers over traditional techniques is the ability to directly control and quantify the amount of variability introduced into the test data and a significant reduction in data collection time.

**METHOD:** Initially, a full-body, 42 degrees of freedom 3D computer model was created and validated using single-subject analysis. One elite female golfer (handicap 0) performed 12 shots with her own driver club. A 6-camera MotionAnalysis infrared camera system operating at 400 Hz recorded the kinematic data of the 27 markers located on the subject and this data were used to drive the computer model in ADAMS/LifeMOD software; model construction methods closely followed that of Nesbit (2005) and kinematic validation replicated Kenny *et al.* (2008). The results illustrate a high level of correlation ( $r^2=0.90$ ) between the kinematic data collected in experimentation and the predicted trajectory of the validation markers of the model. The long-term focus of this work is on the effect of variability at one joint and the resultant change in both outcome measure and kinematics of other joints. However, the first stage is to create the theoretical data sets. To ensure the amount of variability within the theoretical data sets were controlled and realistic, the original data were analysed and used as the base data set. All 12 trials were used - the right knee angle data were all normalised to 101 points, a mean ensemble curve was created from the base data sets and the average standard deviation ( $sd_{avg}$ ) occurring over the whole trial was calculated. The average standard deviation was used to signify the average amount of naturally occurring variability in the standardised trial data, i.e. variability not caused by an external factor such as fatigue. Variability was added to the mean ensemble curve at 20 different levels, the maximum variability curve was created by adding a random number between  $\pm sd_{avg}$  to each data point; as the random number had containment limits it is considered pseudo-random only. Other data sets were created by reducing the pseudo-random number magnitude in 5% decrements to a minimum of 5%  $sd_{avg}$ . As a result 20 data sets were created each with differing variability content; set one  $\pm 100\% sd_{avg}$ , set two  $\pm 95\% sd_{avg}$  etc. As the random number is based on white noise (having a distribution with mean and median of zero), the data occurring at this intermediate stage was not representative of the main characteristics of the base data due to relatively large rates of change between consecutive data points. To remove these inconsistencies all 20 data sets were filtered using a 4th order reverse pass Butterworth filter with a cut off at 12Hz (a cut-off which has

been reported to be useful for golf related data – Mitchell *et al.*, 2003). The filter was not optimised for each data set as it was not the intention to remove the noise, only reduce the issue related to rate of change. As a result, 20 data sets were created each with a different amount of variability imposed on the base data. This variability was based on the characteristics of the original 12 data sets and as such are proposed to be representative and realistic data sets.

Due to the nature of the white noise based pseudo-random data it is essential to examine if the theoretical data sets follow the proposed pattern, e.g. does the data set based on  $\pm 65\%$   $sd_{avg}$  exhibit more variability than that based on  $\pm 45\%$   $sd_{avg}$ . To do this a Bland-Altman analysis (B&A) was completed; B&A is used to compare two measurements of the same variable. As the data presented here is time normalised each data point on the theoretical data set has a corresponding data point on the mean ensemble curve and is therefore considered a valid method of comparison. The 95% limits of agreement (LOA) from the B&A analysis will be used to assess the amount of variability contained within each theoretical data set and the bias will be used to assess if the gross pattern of the mean ensemble curve has been altered.

**RESULTS AND DISCUSSION:** The B&A analysis indicates that the LOA reduces as less variability is added to the data; from 1.44 at  $\pm 100\%$   $sd_{avg}$  to 0.267 at  $\pm 5\%$   $sd_{avg}$  (see Table 1). Further analysis reports an  $r^2$  of 0.9264 when correlating the LOA values and the magnitude of the random number. The bias remains close of zero on each curve, indicating that the variability is equally distributed above and below the ensemble curve.

**Table 1: Bland & Altman Analysis Results for Altered Levels of % of  $sd_{avg}$**

% of $sd_{avg}$	Bias ( $^{\circ}$ )	LOA ( $^{\circ}$ )	% of $sd_{avg}$	Bias ( $^{\circ}$ )	LOA ( $^{\circ}$ )	% of $sd_{avg}$	Bias ( $^{\circ}$ )	LOA ( $^{\circ}$ )
5	-0.016	0.267	40	-0.006	0.533	75	-0.093	0.863
10	-0.006	0.277	45	-0.016	0.620	80	0.048	0.922
15	0.010	0.249	50	0.019	0.737	85	0.108	1.161
20	-0.021	0.380	55	0.092	0.811	90	0.155	1.147
25	-0.025	0.360	60	0.048	0.767	95	-0.202	1.230
30	0.004	0.481	65	-0.014	0.739	100	0.006	1.444
35	-0.051	0.475	70	0.068	0.664			

**CONCLUSION:** The method outlined here, utilising a mean ensemble curve in conjunction with the addition of pseudo-random data and Butterworth filtering enables the practitioner to create valid and representative theoretical data sets which do not remove the main characteristics of the original data sets; as illustrated by the Bland & Altman analysis. The combination of these theoretical data sets, where the amount of variability can be controlled, with a full body 3D computer model of the golf swing leads to the ability to assess the impact of variability on both performance and outcome measures within human movement without having to acquire large amounts of data. The combination of these techniques expedites the reporting process within a sports setting, and allows a dramatic reduction in subject involvement during initial data acquisition compared with more traditional methodologies. Future work will concentrate on the effect the variability of joint angles has on the outcome measures, e.g. ball speed, ball carry, spin rates and performance measures within golf, e.g. weight shift patterns, x-factor stretch and swing plane. The research will further assist biomechanists in assessing the impact of levels of variability on human movement.

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