INVESTIGATING THE USE OF SAMPLE ENTROPY TO DETECT FATIGUE

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Sample entropy can sensitively identify changes in biological signal regularity. The aim of this study was to investigate whether sample entropy could detect such change in human movement which may be attributable to fatigue or other factors. The regularity of kettlebell trajectories from simulated kettlebell sport competition performed by five experienced lifters was assessed using a novel moving window technique. Resultant entropy estimate trajectories indicate sensitivity to changes in regularity. Decrements in grip strength indicate this may be attributable to fatigue though other possibilities exist. The ability to easily model the resultant entropy trajectories is also demonstrated. The technique holds potential for use by practitioners though more work is required before implementation.

KEY WORDS: Sample entropy, regularity, fatigue, kettlebell

INTRODUCTION: Sample entropy, or SampEn(m,r,N), is a statistical method for quantifying the regularity of a signal (Lake, Richman, Griffin, & Moorman, 2002). The technique measures the probability that a data window of m points, that is repeated in a signal of length N points, within a tolerance r, will also repeat for a window of $m+1$ points within the tolerance r. Sample entropy has been used to distinguish between higher and lower skilled athletes (Preatoni, Ferrario, Dona, Hamill, & Rodano, 2010) and observed and surrogate data (Taylor, 2017). Another use has been to identify the onset of illness in infants by assessing regularity changes to heart sinus rhythm (Lake et al., 2002). This ability to sensitively identify critical change in biological signals may have application within the monitoring of human movement.
Like pathology, fatigue can alter the output of the human system. This may manifest as changes to the regularity of observed kinetic and/or kinematic signals. Entropy may therefore provide a tool for detecting fatigue, or fatigue induced changes, in such measures. Kettlebell sport requires participants to perform as many valid repetitions as possible of a kettlebell snatch within 10 minutes (Ross, Wilson, Keogh, Ho, & Lorenzen, 2015). The cyclical motion of the kettlebell and the strength endurance nature of the task offer a potentially fruitful avenue for assessing the ability of entropy to identify possible fatigue related changes in regularity. Therefore, the purpose of this investigation is to ascertain whether sample entropy can identify changes in regularity in the trajectory of a kettlebell, which may be related to fatigue, during simulated kettlebell sport competition.

METHODS: Five skilled male kettlebell sport athletes (1.82 ± 0.07 m, 90.3 ± 11.3 kg, 33.4 ± 7 yrs) participated in this study. The task involved a six minute bout of simulated kettlebell sport competition where participants attempted to perform as many repetitions of the kettlebell snatch as possible within the time limit. One change of hand was allowed at approximately the halfway point consistent with kettlebell sport rules. A retro-reflective marker was place on the front of the kettlebell approximating the centre of mass of the kettlebell. Three dimensional kinematics of the bell were collected using a nine camera Vicon motion analysis system (Oxford Metrics, Oxford, UK) capturing at 250 Hz. Cumulative force applied to the kettlebell across the first and last 14 lift cycles was calculated using inverse dynamics and compared with paired sample T-tests to identify potential effects of fatigue. Similarly grip strength was measured pre- and post-test and also submitted to dependant T-tests. Relevant effect sizes (Cohen's d) were also calculated. This study was approved by the Australian Catholic University Human Research Ethics Committee.
Vertical (z-axis) kettlebell displacement was extracted from the kinematic data. Following frequency and residual analysis the displacement data was filtered using a 4th order

Butterworth low pass filter (6 Hz cut off). Data up to and including the first repetition post hand swap were removed leaving approximately the last three minutes of repetitions. This was done to isolate the data most likely affected by any accumulated central and peripheral fatigue.

To attempt to characterise change in regularity over the exercise bout sample entropy was calculated for a moving window of 10 cycles. This began with the first 10 cycles, ended with the last 10 and covered every sequence of 10 consecutive cycles in between. Windows of lengths 20, 15 and 5 were also tested but a window length of 10 cycles was found to provide the best balance between the length (too short in the 20 cycle condition) and smoothness (too noisy in the 5 cycle condition) of the resultant entropy trajectories. Sample entropy estimates are reliant on the critical values (m,r,N). The length N is set by the period and number of the cycles analysed. The results from several values for m (2 and 3) and r (0.1, 0.2 and 0.3 multiplied by the SD of the signal) were evaluated using the data of one participant and values of m=2 and r=0.1*SD were chosen as they resulted in the most sensitive/discriminative entropy estimate. During analysis it appeared there was a relationship between the change of cycle period and the resultant entropy estimate. As the period alters the value of N for each given window of 10 cycles, each participant's data were interpolated to 1000 points using a Fast Fourier transformation and resultant moving window sample entropy trajectories compared with the unaltered data qualitatively using plots and quantitatively with a Pearson's correlation. This was done to ensure that entropy estimates were the result of more than just changes in the period length of consecutive cycles.

Once the entropy estimate trajectories were ascertained for each participant regression was undertaken to see if the resultant curves could be easily modelled. First, second and third degree polynomials as well as one and two term power curves were fitted to each participant's results with the aim of finding the simplest model to return acceptable goodness of fit.

RESULTS: Differences between cumulative kettlebell force applied during the first and last 14 cycles were non-significant (p > 0.67) with very small effects (d ≤ ±0.10). Grip strength decreased pre- to post-test for both left and right hands (8.2 ± 3.7 kg and 6.6 ± 6.7kg decrements respectively). This decrease was significant for the left hand (p < 0.01) and approached significance for the right hand (p = 0.09). There was a large effect size for the decrease in both the left and right hand (d = 1.2 and d = 1.3 respectively). An example of the vertical trajectory of the kettlebell and overlaid kettlebell cycles can be seen in Figure 1.

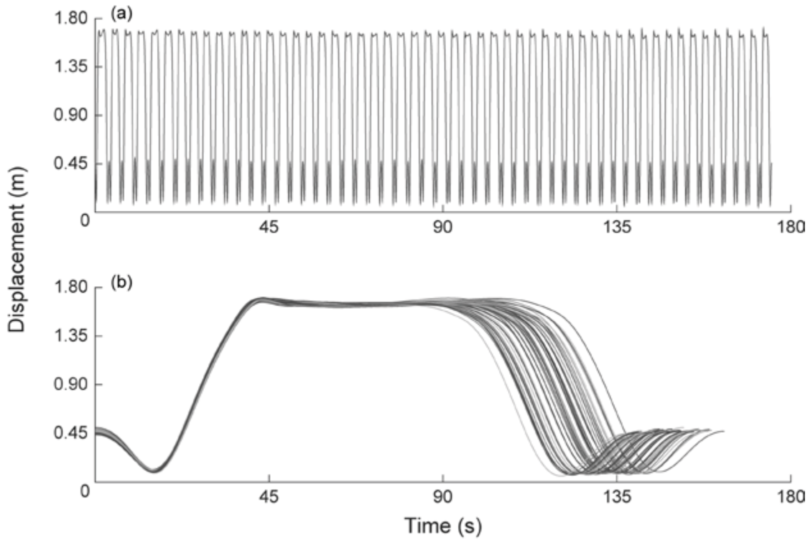

Figure 1. All relevant cycles for one participant represented consecutively (a) and overlaid (b)

Plots of the moving window entropy estimate trajectories of observed data and interpolated data indicated that the shape of the trajectory was relatively consistent between the two conditions. The difference between the two was predominantly represented by a magnitude shift. The direction of this shift depended on whether 1000 points was greater (shift down) or less (shift higher) than the mean number of points making up the observed cycles. An example of this can be seen in Figure 2. Correlation between the two entropy trajectories were all significant ($p < 0.01$) and strong ($r^2 \geq 0.94$). Linear regression yielded a significantly good fit ($p < 0.01$) for four of five participants and mean goodness of fit of $r^2 = 0.60$ (range 0.07 – 0.84).

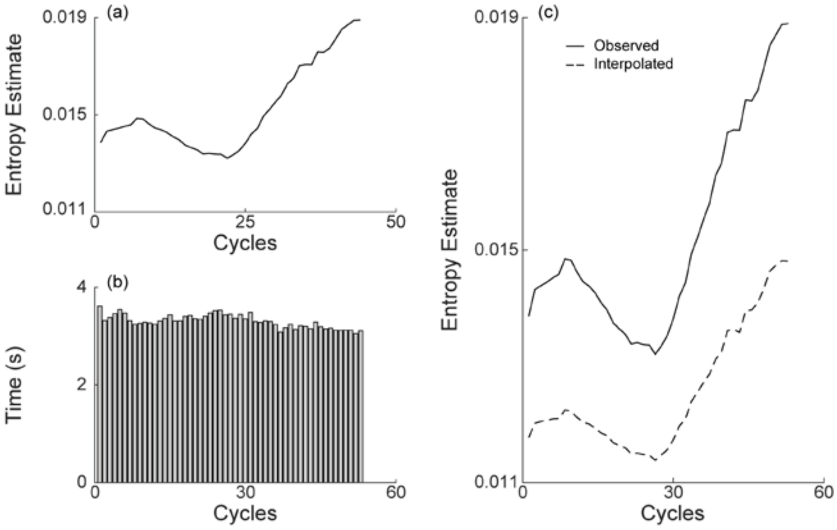

Figure 2. Comparison between entropy estimate (a) and cycle lengths (b). Comparison between entropy estimate of observed and interpolated data (c)

Quadratic regression yielded significant models ($p < 0.01$) for all participants with a mean goodness of fit of $r^2 = 0.90$ (range 0.83 – 0.98). Higher order polynomial regression resulted in diminishing returns for goodness of fit alongside increased model complexity. As such they were not pursued further or included in results. Similarly, power regression (mean r^2 = 0.51 – 0.78) did not perform better than quadratic fits. The resultant moving window entropy trajectories for each participant and respective quadratic model fit can be seen in Figure 3.

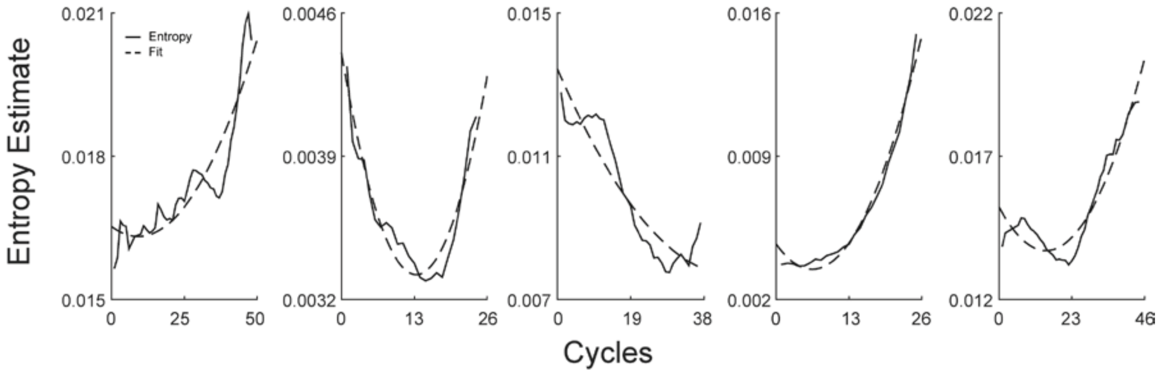

Figure 3. Moving window entropy estimate for participants 1 – 5 (L to R) and relevant model fit

DISCUSSION: The aim of this study was to begin investigating whether sample entropy could detect changes in the regularity of human movement time series which may be attributable to fatigue. Sample entropy was calculated for a moving window of 10 cycles across the last 3 minutes of 6 minute muscular endurance task. Resulting sample entropy trajectories indicate that the entropy estimates for most participants did undergo a noticeable change in trajectory around the last 25 – 50% of performance time (Figure 3). The decrements in grip strength across participants pre- to post-test suggest fatigue was experienced by the lifters. It is possible therefore that the changes in kettlebell displacement regularity characterised by the inflection in the moving window entropy trajectories are the result of fatigue.

There was initial concern in making this observation due to an apparent relationship between cycle period and entropy estimate (Figure 1). However, the highly similar shape of entropy estimate trajectories for both the observed and interpolated (standardised period) data as

well as correlation results suggest that this may not be the sole reason for regularity changes. Furthermore, the other kinematic trajectories (x and y axes) indicated no similar relationship. As the vertical displacement of the kettlebell is the primary movement outcome of this sport (a repetition is only counted once the kettlebell is 'locked out' overhead) it can be expected that variability is low for this trajectory. Movement outcomes and mechanically important facets of skills consistently display reduced variability compared to other aspects of movement (Taylor, 2017). Furthermore, the vertical amplitude of the kettlebell is constrained somewhat by anatomical ranges of motion, both at the highest point and during the cycle completion/initiation as the kettlebell passes through the legs. This constraint may leave period modulation as the primary means of any change to the regularity of cycles over time. Magnitudes of the entropy estimates indicate kettlebell trajectories are highly consistent (sample entropy estimates range between 0 and 1 where 0 is complete regularity). However, the plots in Figure 1 illustrate that despite this, variations in the cycle curves exist which are not limited to changes in period.
It appears though that even when regularity changes are small moving window entropy estimates can detect them. Whether this can be confidently attributable to fatigue will require further work. Other potential sources of regularity alteration may lie in changes in the effort of the lifters as they approach the end of the bout (e.g. a 'sprint' finish). Even if this is the case it appears the entropy estimates are sensitive enough to identify this change within a highly regular movement time series. Further trialling of the technique is required in settings where the onset or existence of fatigue can be well documented. Furthermore, activities where the period of the cycles are more constrained, such as cycling and multi-crew rowing, as well as application to joint or segment kinematic data and kinetic data may prove more informative.
Another potential benefit of the technique may lie in the ease with which it can be accurately modelled. For all participants a parabola was able to be fitted to the moving window entropy trajectory with strong goodness of fit. This raises the possibility of being able to predict future outcomes or to identify when elements such as training or tactical adaptation result in a change to the expected entropy trajectory. While the quadratic regression provided a strong fit a relatively clear inflection point in the data existed for most participants (Figure 3). The moving window entropy trajectories may therefore also be modelled well by two linear regressions, one for data up to the inflection and one for after it. Data departure from one regression to the next may better isolate the onset of any changes in regularity. If related to fatigue, this inflection point may also offer a focus for training, where the goal could be to shift it right, similar to some physiological variables such as anaerobic threshold.

CONCLUSION: This study demonstrated that it may be possible to employ sample entropy to effectively and sensitively identify changes in the regularity of human movement. These changes in regularity may be attributable to fatigue or other factors which are otherwise not easily identifiable. The sensitivity of the measure, the ease of modelling and the existence of inflection in the moving window entropy trajectory provide possibilities for athlete monitoring, performance analysis and planning as well as training feedback. Further work is required though to fully understand the strengths, weaknesses, intricacies and scope of the method.

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