Title: The effect of signal acquisition and processing choices on ApEn values: towards a "gold standard" for distinguishing effort levels from isometric force records.

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ABSTRACT

Approximate Entropy (ApEn) is frequently used to identify changes in the complexity of isometric force records with ageing and disease. Different signal acquisition and processing parameters have been used, making comparison or confirmation of results difficult. This study determined the effect of sampling and parameter choices by examining changes in ApEn values across a range of submaximal isometric contractions of the First Dorsal Interosseus. Reducing the sample rate by decimation changed both the value and pattern of ApEn values dramatically. The pattern of ApEn values across the range of effort levels was not sensitive to the filter cut-off frequency, or the criterion used to extract the section of data for analysis. The complexity increased with increasing effort levels using a fixed '*r*' value (which accounts for measurement noise) but decreased with increasing effort level when '*r*' was set to 0.1 of the standard deviation of force. It is recommended isometric force records are sampled at frequencies >200 Hz, template length ('*m*') is set to 2, and '*r*' set to measurement system noise or 0.1 SD depending on physiological process to be distinguished. It is demonstrated that changes in ApEn across effort levels are related to changes in force gradation strategy.

KEYWORDS: complexity, isometric muscle force, first dorsal interosseus

INTRODUCTION

A healthy physiological output signal results from the integration of many processes, and allows for a full range of responses to any physiological demands [1]. As the physiological systems underlying these processes degenerate as a result of ageing or pathology, the possible values of the physiological output become restricted, which results in a decreased complexity [2, 3]. The measurement of changes in complexity are therefore useful in identifying early and pre-clinical degeneration, and, conversely, successful rehabilitation and preventative strategies [3]. Here complexity refers to a signal which has detailed structure. Approximate Entropy (ApEn) is a statistic that quantifies the complexity and regularity of physiological time series [4]. For example, a sine wave is regular and therefore has an ApEn value close to 0; while white noise consists of random independent samples and has an ApEn value close to 2.

The ApEn statistic derives from the Kolmogorov-Sinai entropy in an information theory sense, but, whereas the latter requires large amounts of data to achieve convergence and is not robust to noise, the former has the advantage for physiological signals that it can account for noise, is robust to outliers, and is applicable to relatively short data lengths [5]. ApEn is designed for use as a comparative measure such that for a defined template "length", '*m*', and noise amplitude, '*r*', a more regular (less complex) data series of length *N* points has a lower ApEn(m,r,N) value (i.e. closer to zero) than a more irregular data series of the same length [6].

ApEn has also been used to quantify complexity in human motor behaviour, and in particular in isometric force records from voluntary muscle contractions [7, 8]. As the force fluctuations are influenced by changes in motor unit activity [9] quantifying the ApEn of an isometric force record provides insight into motor control strategies and how they may change with ageing, disease, and training interventions [10]. For the comparison of older with younger adults, the differences in ApEn are consistent with the age-related loss of complexity hypothesis, though these changes may be a characteristic of isometric tasks only [7, 11]. ApEn has also been used to construct an entropy based theory of adaptation to different motor task requirements under different conditions of environmental information [8]. The use of ApEn therefore forms the basis for a number of hypotheses and explanations in relation to the production of isometric force, and theories of motor behaviour, control, and ageing.

Given the scope of these theories, it is important that there should be comparability between studies. However, signal acquisition and processing parameters have varied between studies involving isometric force production (Table 1), for example the sample frequency used varies by an order of magnitude, and the filter cut-off frequency varies by two orders of magnitude. The present study was motivated by an inability to replicate previously reported patterns of ApEn values across effort levels [12] where different signal sampling and post-processing characteristics were used. No previous study has examined how changing these characteristics affects the conclusions drawn from isometric force records. It is entirely possible that signal acquisition and processing parameters may interact with the ApEn parameters [13].

The ApEn statistic is a biased estimator of the limiting parameter as are virtually all non-linear statistical estimators [6]. Pincus [4] has demonstrated that with appropriate parameters ApEn can distinguish between different signal types. Chon et al. [14] proposed that '*r*' should be set such that the ApEn value is maximized. However, ApEn is intended for use with a fixed experimental protocol, fixed data length, and fixed '*m*' and '*r*' parameters so that comparisons can be made between subjects and or conditions. It is not expected that the absolute ApEn value can be compared for different signal acquisition and processing settings. Consequently the approach used here was to determine the effect of these settings by empirically comparing the pattern of mean ApEn values across a range of isometric effort levels for a group of subjects. A similar approach has been used in other areas such as endocrinology [13]. By collecting the force signals at each effort level for each subject with high force and temporal resolution post-processing then allows the simulation of the effects of various parameter choices. Therefore, the purpose of this study was to answer, for the first time, the following questions to determine how conclusions drawn from data may change with different parameter choices.

1) What frequencies are present in isometric force signals?

2) What is the effect on ApEn of altering the parameters '*r*' and '*m*' for isometric force records?

3) What is the effect on ApEn of different sampling frequencies?

4) What is the effect on ApEn values of different filter cut-off frequencies?

5) Are the changes in ApEn with decimation an effect of having fewer data points or is it related to the frequencies that are captured?

6) What is the effect of using a minimum variance criterion to select the section of data for analysis, compared with alternative criteria?

The eventual aim was to identify a “gold standard” for the acquisition and processing of isometric force records, where the purpose is to distinguish effort levels from each other.

Having identified suitable acquisition, processing and parameter choices the purpose was then to identify how the regularity of the force signal, as quantified by ApEn, varied with effort level over a range from 5% of maximum voluntary contraction (MVC) to 75% MVC.

MATERIALS AND METHODS

Participants

Twenty-three, neurologically healthy subjects (range 18-72 years; 13 females and 10 males) were recruited to the study. All subjects were assessed for hand dominance by the Edinburgh Handedness Inventory [15], and all testing was performed on the non-dominant hand. Potential subjects were excluded if they had history of a serious hand injury, suffered from arthritis affecting the hand, had untreated high blood pressure or were taking any medications known to have neurological side effects. If required subjects wore their prescription lenses through all testing procedures. All subjects gave written informed consent for the experimental procedures, which had been approved by the Aberystwyth University Ethics Committee for Research Procedures.

Testing Apparatus

Participants sat upright on a non-adjustable chair (height = 45 cm) facing a 60 cm computer monitor, which was placed approximately 70 cm away and centered both horizontally and vertically from the eyes. The participants non-dominant hand was pronated and lay flat, resting on a custom made metal plate to which a load cell was attached. The non-dominant elbow was flexed to 90 degrees, and the upper arm slightly abducted. A restraining plate was positioned between the second and third phalanges of the hand to restrict motion of the remaining phalanges. The load cell and thumb rest were positioned so that the load cell was level with the lateral side of the proximal inter-phalangeal joint with the angle between thumb and index finger being approximately 80 degrees when the finger was in contact with the load cell (Figure 1). This set-up permitted measurement of the forces during index finger abduction, an action produced entirely achieved by the first dorsal interosseus. The initial trial hand position was traced so that hand position was standardised from trial to trial.

<<<Insert Figure 1 Around Here.>>>

The signal from the load cell (HBM, PW6-CC3MR/10 kg, Hottinger Baldwin Messtechnik, Harrow, UK Ltd.; sensitivity 2.2 mV/V) was passed through an HBM AED-9101-B full bridged transducer (Hottinger Baldwin Messtechnik, Harrow, UK). The force signal was sampled at 1200 Hz, designed to reflect the sample frequency used if force and electromyographic data are collected synchronously (e.g. [10]).

Familiarisation Procedure

Each participant was asked to attend a familiarisation session a few days prior to the test day. At the beginning of each session participants performed a warm-up of light finger exercises such as flexing and extending the fingers. During the familiarisation session the participant's maximum voluntary contraction force (MVC) was measured in order to avoid fatigue during the experimental testing session. To measure MVC the participant increased the finger abduction force gradually over approximately 5 seconds until they were pushing as hard as possible and then held the maximum force possible for 2-3 seconds. The force applied to the load cell was displayed on the monitor in white pixels. The time count was displayed on the screen and verbal encouragement was given during each trial. After two practice trials a further three maximum effort trials were performed. Between each trial the participant was given a 3 minute rest. The maximum force from the three recorded trials was the MVC.

Following this each participant practiced a number of the force targeting trials, which included familiarisation with the targeting of the force trajectory at force levels varying from 5% to 75% of MVC. The display was re-scaled for each subject so that the force target was displayed as a percentage of maximum from 0-100% to avoid possible effects on resolution due to scaling.

Testing Procedure

At a subsequent session participants produced isometric contractions at 5%, 10%, 25%, 40%, 50% and 75% of their MVC for ten seconds. A three minute rest was given after trials of 50% and 75% MVC, otherwise a one minute rest was given. The order of presentation of the effort levels was randomised. Participants were informed what the force target would be prior to each trial and were instructed to ramp-up the contraction from 0% as quickly as possible to the target.

The target was a force level identified by two red lines displayed on a computer monitor, the top line two pixels thick and bottom line four pixels thick. The gap between the red lines was scaled to be ± 5% of the target force. In order to maintain a visible gap between the lines at the lowest force levels a minimum gap of a six pixels was used, which represented an error window of ±20% at 5% MVC, and ±10% error at 10% MVC. The participant viewed their force trajectory as a white force time trajectory two pixels thick moving from left to right across a black background. The participants were instructed to keep the white trajectory line between the red lines, but were told to focus on keeping the line as 'straight and steady' as possible.

Post Processing

All data processing was performed using custom software written in Matlab v9.9 (MathWorks, Inc., Natick, MA). Electrical noise was removed using a 49.0-51.0 Hz 4th order (bi-directional) Butterworth notch filter. Unless otherwise stated, a rolling minimum variance window was used to select the steadiest three second section of each data set for subsequent analysis. ApEn was computed for each trial using the method described by Pincus [4]. ApEn quantifies the negative natural logarithm of the conditional probability that a template is repeated during a time series. ApEn(m,r,N), takes sequences of m data points and determines the logarithmic likelihood that this sequence is similar to other sequences of data points in the data set. Matching templates that remain similar (i.e. within the tolerance, r) are then counted, the number of matches to the ith template of length m is designated B_i. Then the number of these matches that remain similar for the m+1th point is counted, this number for the ith template is designated A_i. When comparing sequences they are considered to be similar if the sequences differ by an amount greater than the noise threshold r. The approximate entropy can then be computed from,

$$ApEn(m,r,N) = \frac{1}{N-m}\sum_{i=1}^{N-m} \log \frac{A_i}{B_i}$$

Where,

N – number of data points in time series

m – length of template

A_i – number of matches of the ith template of length m+1 data points

B_i – number of matches of the ith template of length m data points

Several different processing conditions were applied to the force data in post-processing to answer the questions posed about the effect of signal acquisition and processing choices on the ApEn values. The effect that each condition had on calculated ApEn values was determined from the mean results and the associated confidence interval for all subjects across different isometric effort levels. The processing conditions applied were as follows.

1) What frequencies are present in isometric force signals? Frequency analysis of the measurement system from trials with no load and a known load on the force sensor, and the spectra of the subjects' trials was carried out in order to identify frequencies present in the signal that are due to physiological processes.

2) What is the effect on ApEn of altering the parameters '*r*' and '*m*' for isometric force records? The parameter '*r*' was altered from the Root Mean Square (RMS) of the measured noise (*r*=1.13N, determined by collecting force signal data with no force exerted and with a known load), to using 0.1 of signal standard deviation (SD), and 0.2 SD of the force signal of each trial, '*m*' was increased from 2 to 3.

3) What is the effect on ApEn of different sampling frequencies? *The original signal sampled at 1200 Hz was decimated to 600 Hz, 200 Hz, 100 Hz and 30 Hz to simulate lower sampling frequencies. In the decimation process the original data set is filtered to remove signal frequency components above the Nyquist frequency to be simulated, and then the signal is resampled. To mirror an approach sometimes used in the literature the 1200 Hz was also downsampled, that is: resampled to produce a 100 Hz signal, but without the filtering.*

4) What is the effect on ApEn values of different filter cut-off frequencies? The original signals were low-pass filtered using 4th order bi-directional Butterworth filters, with cut-off frequencies of 100 Hz, 80 Hz, 70 Hz, 60 Hz, 50 Hz, 30 Hz and 25.6 Hz. The cut-off frequencies were selected to mirror values used in the literature and the frequencies associated with motor unit activity (Table 1).

5) Are the changes in ApEn with decimation an effect of having fewer data points or is it related to the frequencies that are captured? The size of the minimum variance window was altered to capture the number of data points that equalled the total number of data points in each decimated data set. For example, decimating a three second length of data sampled at 1200 Hz to 30 Hz reduces the number of points from 3600 to 90 data points. Therefore the minimum variance window was adjusted to collect just 90 data points. This method was used to simulate the collection of 1800, 300 and 90 data points (the number of data points equivalent to sampling at 600 Hz, 100 Hz and 30 Hz respectively). In addition, the steadiest five seconds, three seconds and half a second of the force data (starting from the fourth second) were selected from each trial in order to assess the effect of varying N on ApEn values.

6) What is the effect of using a minimum variance criterion to select the section of data for analysis, compared with other criteria? A 3 s window extracted using a minimum variance criterion was compared to a 3 s window starting from the fourth second, and to a 3 s window starting at the sixth second, and to half second windows starting at the fourth, sixth or eighth second of data. Since the first three seconds of data was always

removed to allow for ramping up to the correct force level, there were seven seconds of data (from the 3rd to the 10th second) available for analysis.

Finally, once reasonable values for the parameters had been chosen, the relationship between effort level as a percentage of MVC and regularity as quantified by ApEn was determined. An Analysis of Variance and post-hoc Tukey tests were used to identify for which force levels the regularity differed. The significance level for all statistical tests was set at p=0.05.

RESULTS

Typical force-time records are shown for a contraction at 5% of MVC, and a contraction by the same subject at 75% of MVC (Figure 2).

<<Insert Figure 2 around here>>

1. What frequencies are present in isometric force signals?

The frequency spectra of force for contractions at 5 to 75 % had the majority of the power below 15 Hz, but the power in the signals between 15 and 30 Hz did increase with changing percentage of MVC (Figure 3). For example, the proportion of the signal power in the 0 to 15 Hz band compared with the 15 to 30 Hz band was twice as great for the 75% signal compared with the 25% signal. The power spectrum for the force sensor was constant and low across all frequencies (Figure 3a), and so did not demonstrate changes in power with increases in frequency, thus the changes in signal power content with increasing percentage of MVC were biological in origin.

<<Insert Figure 3 around here>>

2) What is the effect on ApEn of altering the parameters '*r*' and '*m*' for isometric force records?

Changing the '*r*' parameter had a large effect on the pattern of ApEn results across the range of effort levels (Figure 4). Using a value for '*r*' which was obtained from an analysis of the amplitude of the noise of the transducer resulted in a sigmoid like curve across the range of effort levels. However, increasing the value of the '*r*' parameter to 0.2 of the standard deviation of each signal resulted in a flattening of the pattern of ApEn values across the range of effort levels. Changing the '*m*' parameter from 2 to 3 reduced the ApEn values but preserved the pattern of values across the force levels (Figure 5).

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3) What is the effect on ApEn of different sampling frequencies?

Down-sampling and decimation of the data to replicate sampling frequencies below 200 Hz reversed the trend of ApEn values across the range of effort levels (Figure 6).

<<Insert Figure 6 around here>>

4) What is the effect on ApEn values of different filter cut-off frequencies?

For sample rates above 200 Hz, changing the filter cut-off frequency had little effect. Very small decreases in the absolute ApEn values were seen with decreases in the filter cut-off frequency from 80 to 25.6 Hz (Figure 7). The patterns of ApEn values across the range of effort levels were identical.

<<Insert Figure 7 around here>>

5) Are the changes in ApEn with decimation an effect of having fewer data points or is it related to the frequencies that are captured?

When the data is downsampled to produce a signal sampled at 100 Hz or 30 Hz, the ApEn pattern changes considerably (Figure 8a). However, a three second data record at 100 Hz is 300 data points long, and at 30 Hz is 90 data points long. When sections of data of length 300 points, and 90 points are taken from the original signal sampled at 1200 Hz without downsampling, it can be seen that the pattern of ApEn results over the effort levels does not change, although the absolute ApEn values change slightly (Figure 8a). This suggests that the dramatic change in pattern seen when the data is decimated or downsampled (Figure 6) is related to the frequencies captured and not the number of data points analysed.

6) What is the effect of using a minimum variance criterion to select the section of data for analysis, compared with an alternative criterion?

When a fixed section of the data record is taken, for example from the 3rd to the 6th second, as opposed to using the minimum variance criterion to select the same data length, there is very little effect on either the absolute ApEn values, or the pattern of values across the effort levels (Figure 8b).

<<Insert Figure 8 around here>>

Finally, with '*r*' set at the level of transducer noise, '*m*' set to 2, the sample rate set to 1200 Hz, and a data length of 3 seconds selected using the minimum variance criterion, there was a significant effect for effort level on ApEn(2, (F=44.39; d.f.=5, 105; $p<0.001$). Post-hoc Tukey comparisons showed that effort levels of 5, 10 and 25%

MVC were significantly different from effort levels of 40, 50 and 75% MVC ($p<0.001$). In general the ApEn value increased with increasing effort level (Figures 3-7). Conversely, with '*r*' set at 0.1SD the ApEn value generally decreased with increasing effort level (Figure 4) ($F=16.69$; d.f.=5, 110; $p<0.001$). Post-hoc Tukey comparisons showed that the effort levels of 5% and 10% MVC were significantly different from the other effort levels, and that 25% and 40% MVC were significantly different from 50% and 75% MVC ($p<0.001$).

DISCUSSION

This study determined the effect of different sampling and post-processing choices on the pattern of ApEn values for isometric force records across a range of effort levels produced by the First Dorsal Interosseus in order to identify what effect these may have on conclusions drawn when using ApEn to differentiate between force levels. This study has shown that choosing an appropriate value for the '*r*' parameter in the ApEn algorithm is very important. The role of this parameter is to account for measurement system noise. The choice of '*r*' for a given process or physiological setting, is influenced by physiological attributes (the focus of the present study), the series length, N, and the sampling frequency. The sampling frequency also strongly determines the entropy value due to the mathematical underpinnings of the calculation of ApEn.

When examining the variability of beat by beat heart rate data it has been recommended that '*r*' be set to between 0.1 and 0.25 of the SD of the time series [5].

However, for heart rate data it can be more difficult to estimate the noise of the measurement system since it arises from several sources. For a force transducer that is well shielded and has a differential input amplifier the noise level should be very low, and measurable. In addition, when comparing beat by beat data, it is likely that the standard deviation of data from different subjects is fairly similar [16]. This is partly due to the physiological limits of the heart which mean that the range of frequencies is low (the extreme range of 30 to 220 beats per minute is equivalent to a range of just 0.5 to 3.67 Hz). In contrast, the standard deviations of the force signals here increased by orders of magnitude moving from 5% to 75% MVC. This means the pattern of ApEn values is flattened across the range of effort levels as '*r*' is increased through 0.1 to 0.2 SD (Figure 4). The proposal of Chon et al. [14] that '*r*' should be set such that the ApEn value is maximized, if applied across the full set of force records for all effort levels and subjects was approximately the same as the amplitude of the transducer noise, i.e. the low and fixed 'r' value (1.13N) used here.

A primary finding of this study was that a fixed 'r' value reflecting measurement system noise results in a strong discrimination between different processes in the analysed signal, which is consistent with previous work [13]. An important point is that ApEn with a fixed '*r*' value captures changes in both complexity and variance [17]. It is often the case that ApEn increases with increasing variance [17]. To decouple ApEn from the variance, Pincus and Goldberger [17] suggested that 'normalized regularity' could be obtained by setting '*r*' to a fixed percentage of the standard deviation. Both versions of ApEn have their uses but have a slightly different focus from each other [18].

The direction of the relationship between ApEn and effort levels reverses when '*r*' is reduced from 0.1 SD to a level equivalent to measurement system noise (r=1.13N). A similar phenomenon was shown by Pincus and Huang [6] who mathematically constructed a pair of processes denoted the 'flip-flop pair'. Their conclusion was that different relative dynamic characteristics can be manifested as the resolution (controlled by reducing the '*r*' value) is altered. Using this reasoning it may be concluded that with a fixed '*r*' that is similar to measurement system noise, it is possible to distinguish between effort levels above 40% and below 25% of MVC. When the normalized regularity is assessed (i.e. using '*r*' set to 0.1SD) it is possible to distinguish between effort levels below 10% versus effort levels above 25% MVC, and to distinguish between 40% versus 75% MVC. However it is not possible to distinguish between all effort levels using only one '*r*' value.

The second key setting identified here was the choice of sample frequency. Figure 6 shows that sample frequencies below around 200 Hz, whether obtained by decimation (filtering before downsampling to prevent aliasing) or simple downsampling (taking every n^{th} point without prior filtering) changes, and for very low sample rates, completely reverses the pattern of mean ApEn values across the effort levels. Veldhuis et al. [13] used a similar approach to the present study when examining the effect of varying sampling frequency on ApEn applied to hormonal secretory patterns. Their study also showed that a high sampling frequency is required for delineation using ApEn of records arising from models with different dynamics.

The pattern of decreasing complexity with increasing effort level seen with the 30 Hz sample rate seems unrealistic when the appearances of the plots for 5% and 75% of MVC are considered (Figure 2). Furthermore, this sample rate would not allow frequencies above 15 Hz to be captured without aliasing. For frequencies above 200 Hz, the pattern of mean ApEn values across the effort levels is preserved, although a reduction in the actual values is seen. Comparison of Figure 6 with Figure 8 shows that the change in pattern for low sample frequencies is not simply due to the reduction in the number of data points when a lower sample rate is used. For example, the pattern of mean ApEn values clearly changes when the sample frequency is changed to 100 Hz, at this frequency 300 data points constitute the 3 second window, whereas at 1200 Hz the three second window is 3,600 data points long. However, when the ApEn value of 300 sequential data points from the data series sampled at 1200 Hz is computed it can be seen that although the ApEn value is reduced, the pattern of mean values across the effort levels is preserved. The greater relative sensitivity of the ApEn algorithm to the sample frequency as opposed to the number of data points should not be surprising given the theoretical relationship between entropy rate and scalar multiples of sample frequency [17].

It can be seen from Figure 8b that, once a steady state force has been achieved, the criterion used to select the data window for analysis has little effect on either the pattern of ApEn values or the actual ApEn values. The length of the data series also has little effect on the pattern of ApEn values, though for very short data series the

ApEn values are slightly reduced for the highest effort levels. Also, once a suitably high sample rate, and a suitable value for the '*r*' parameter had been set, it was found that the pattern of mean ApEn values was robust to changes in the '*m*' parameter. Finally, once a suitably high sample rate, and a suitable value for '*r*' had been set, the filter cut-off frequency had little effect on either the pattern or the actual values; this may be expected since the '*r*' parameter, if appropriately set, acts as a filter. The robustness to a range for the '*m*' parameter is reasonable given the formulation of the ApEn algorithm [17]. It is reassuring that the pattern of results is also reasonably robust to small alterations in the location and length of the window of data for analysis.

ApEn has been widely used to draw conclusions about the structure of isometric force records and possible differences, for example, with age [19], task [20], pathology [21], and feedback [22]. However, previous studies have used very different signal acquisition and processing settings and have used different parameter settings, even for the same task. The results of this study show that certain sampling and parameter choices can completely reverse conclusions with respect to the regularity of isometric force records at different effort levels. The present study did not identify the same inverted U relationship reported by Slifkin and Newell [12]. While the present study involved finger abduction, which is entirely achieved by the first dorsal interosseus, the Slifkin and Newell [12] study measured index finger flexion, for which it is the prime but not the sole mover. However, given the results of the present study, it is also possible that the discrepancy is due to their sample rate of 100 Hz, which, based on the present findings, would reduce the ApEn value of the highly variable trials at the higher effort levels towards zero.

The difference in regularity with fixed '*r*', ApEn(m=2, r=1.13N, N=3600), between effort levels above and below 40% found in the present study may be associated with the different force gradation strategies for the first dorsal interosseus [12, 23]. Below 30-40% MVC force gradation is primarily achieved by motor unit recruitment, at higher effort levels it is achieved primarily by rate coding [24]. As previously described, ApEn(m=2, r=1.13N, N=3600) reflects the change in regularity and variance jointly. It is noteworthy that the degree of regularity is comparable at 40 and 75% of MVC, despite the magnitude of the fluctuations (quantified by the standard deviation of force) being twice as high for 75% MVC and statistically significantly different to 40% MVC. Conversely ApEn(m=2, r=0.1SD, N=3600) is lower for 75% than for 40%, suggesting that the apparently greater randomness using ApEn(m=2, r=1.13N, N=3600) is linked to the higher variance of the force record at 75% MVC.

The results of the present study suggest that a change in the force gradation strategy can be identified using ApEn with '*r*' fixed and equivalent to the measurement system noise. This metric shows that in the region of motor unit recruitment, the force record during isometric contraction is highly ordered, but exhibits less regularity or greater randomness in the region of rate coding. Furthermore it is possible to distinguish between effort levels below 10% and above 10%, and to distinguish between 40% and 75% MVC by using ApEn with '*r*' set to 0.1SD. This metric may reflect an inflection point in the motor unit firing rate versus effort level relationship. Such inflection points can be seen in the motor unit firing rate versus force level plots presented by De Luca and Erim [25]. While EMG studies indicate the patterns of motor unit recruitment in the FDI [26], simulation studies of motor unit activation patterns and the corresponding changes in the nature of force output demonstrate that these variations are caused by multiple mechanisms [9]. There are other mechanisms which will contribute these force fluctuations, for example muscle forces will cause corresponding changes in tendon stretch causing changes in muscle length and therefore muscle force. At low muscle forces these tendon length changes may not be influential because of the low stretch caused in the toe-region of the tendon stress-strain curve [27]. The pattern of results seen in this study characterize the FDI, but the relationship between motor unit firing rate and force relationship differ between muscles, for example there is a distinct difference in this pattern for the FDI [24] and the Vastus Medialis [28]. The methods proposed in this study would be applicable to other muscles, but may potentially reveal different mechanisms associated with force variability.

In conclusion, based on the findings of this study, when computing ApEn it is recommended isometric force records are sampled at frequencies >200 Hz, '*m*' is set to 2, and '*r*' is set using estimated measurement system noise or 0.1SD depending on the effort levels to be distinguished. Using these values, it has been shown that significant ApEn differences existing at effort levels corresponding to a change in force gradation strategy. The relationship between the structure of the variability and the force gradation strategy for this muscle provides a basis for using ApEn to detect and understand changes in neuro-muscular physiology with ageing, pathology and training.

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Table 1: Sample and filter cut-off frequencies used in some force steadiness studies.

Study	Muscle Tested	Sample Frequency (Hz)	Filter Cut-off (Hz)
Slifkin and Newell [12]	First Dorsal Interosseus (Flexion)	100	30
Sosnoff et al. [29]	First Dorsal Interosseus (Abduction)	100	25.6
Rose et al. [10]	Akle dorsi- and plantar-flexors	1000 down-sampled to 200	1000
Svendsen and Madeleine [30]	Elbow and wrist flexors	500	10.5

LIST OF FIGURES

Figure 1: Experimental set-up showing hand and index finger position.

Figure 2: Typical isometric force records from one subject at 75%, 50%, 25%, and 5% MVC.

Figure 3: Typical frequency spectra for a) the steady state section of isometric force records at various effort levels, and b) for two exemplar effort levels and the transducer noise when loaded with a fixed mass (expanded view). Note that the noise is so low in magnitude compared to the other signals that it is barely visible in a).

Figure 4: Mean (error bars show 95% confidence interval for the mean) ApEn values across the range of effort levels when the '*r*' parameter is set equal to the amplitude of the transducer noise, or equal to 0.1 or 0.2 times the standard deviation of the force record, and '*m*'=2 and N=3,600.

Figure 5: Mean (error bars show 95% confidence interval for the mean) ApEn values across the range of effort levels when the '*m*' parameter is set to 2 or 3, and '*r*' is set to the amplitude of the transducer noise and N=3,600.

Figure 6: Mean (error bars show upper bound of 95% confidence interval for the mean) ApEn values across the range of effort levels when the sample frequency is

1200 Hz (Undec) or decimated to 600 Hz (Dec600) to 200 Hz (Dec200) to 100 Hz (Dec100) to 30 Hz (Dec30) or is simply downsampled to 100 Hz (DOWN). The '*m*' parameter is set to 2, and the '*r*' parameter is set to the amplitude of the transducer noise.

Figure 7: Mean (error bars show upper bound of 95% confidence interval for the mean) ApEn values across the range of effort levels when the sample frequency is 1200 Hz and the filter cut-off frequency is set to values between 25.6 Hz and 80 Hz. The '*m*' parameter is set to 2, and the '*r*' parameter is set to the amplitude of the transducer noise and N=3,600.

Figure 8: Mean (error bars show upper bound of 95% confidence interval for the mean) ApEn values across the range of effort levels for a) data decimated to replicate sampling at 100 and 30 Hz and also data records of the same length (number of points) but sampled at 1200 Hz, and b) data records sampled at 1200 Hz of various lengths. In (b) the data is either extracted using a minimum variance criterion, or is taken from a fixed section of the data: for the 5 second record this is from 4 to 9 seconds, for the 3 second record this is from 4 to 7 seconds, for the 0.5 second record this is either from early in the record (4 to 4.5 seconds) or from late in the record (6 to 6.5 seconds). The '*m*' parameter is set to 2, and the '*r*' parameter is set to the amplitude of the transducer noise.

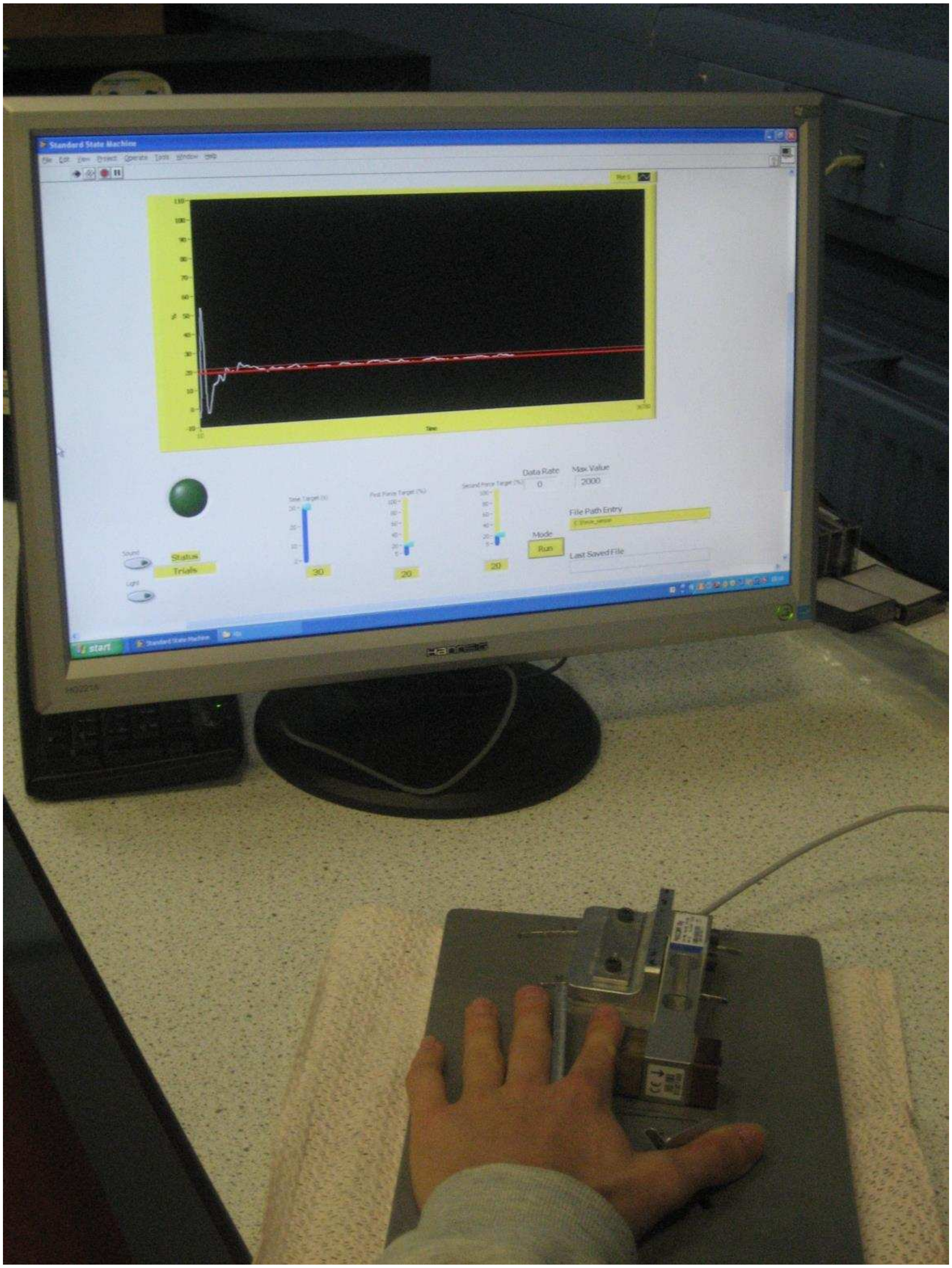
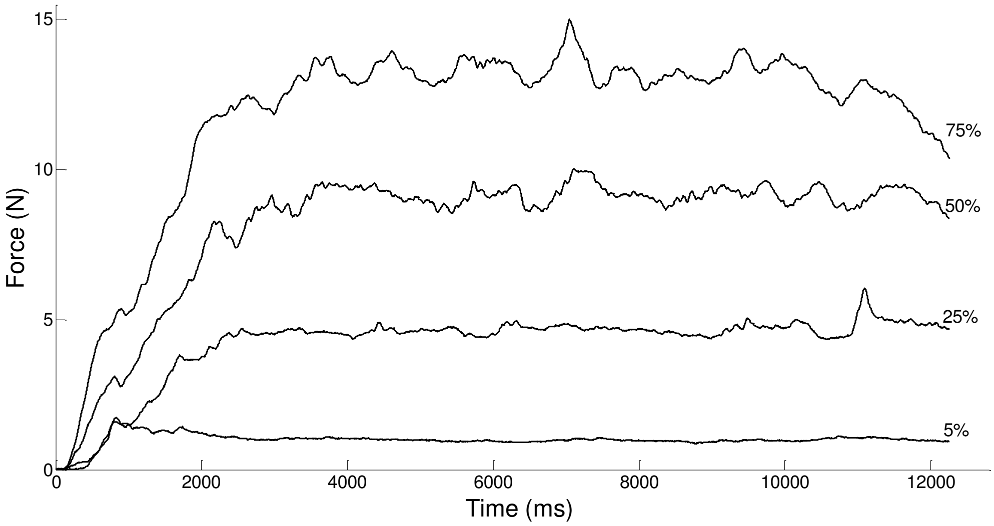
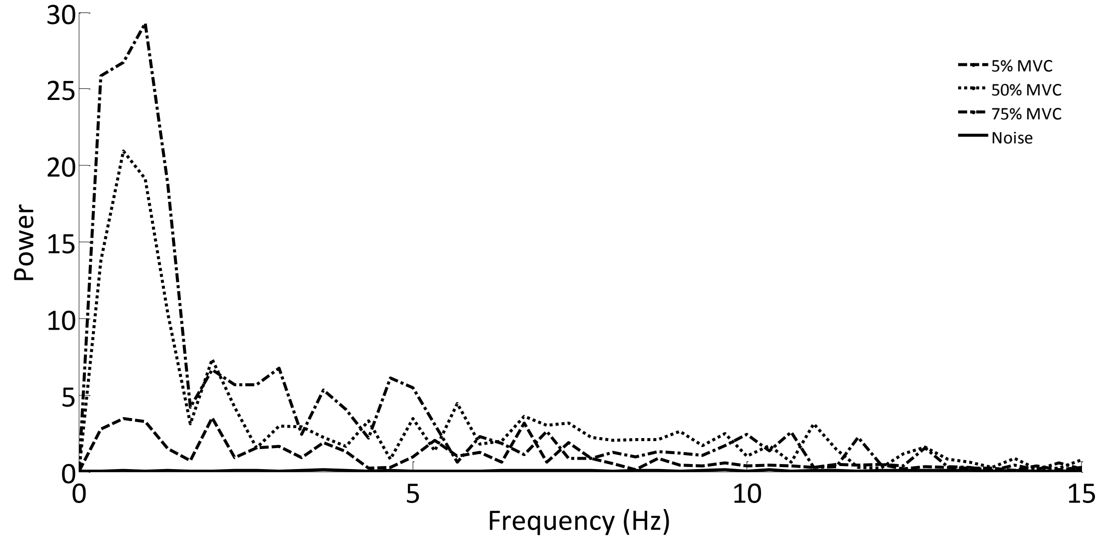

Standard State Machine
Data Rate
0
Max Value
2000
File Path Entry
Mode
Run
Last Saved File
Status
Trials
Sound
Light
30
20
20
start

Figure 1:



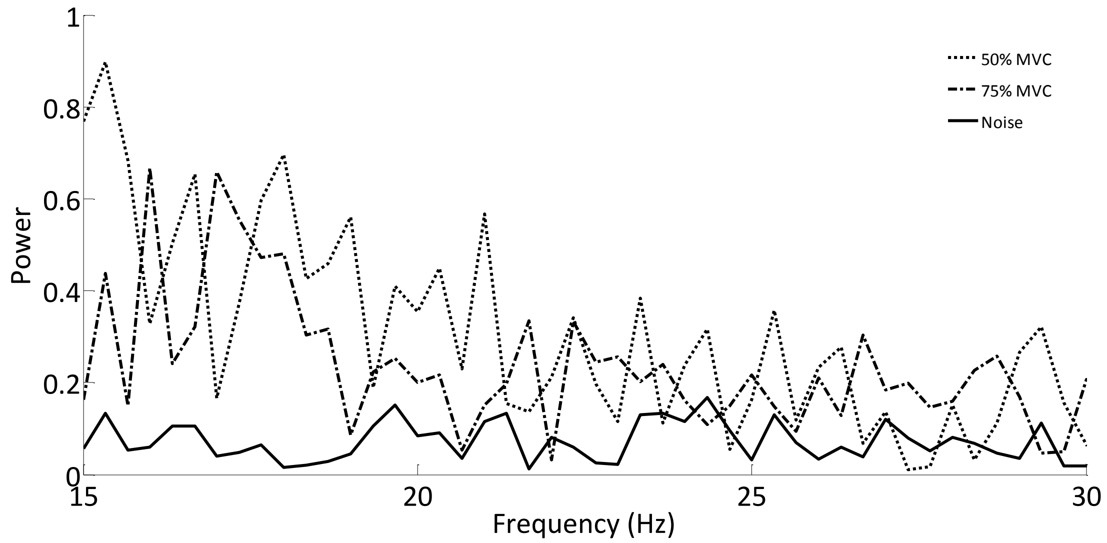
Force (N)
Time (ms)
0
5
10
15
0
2000
4000
6000
8000
10000
12000
75%
50%
25%
5%

a)



30
25
20
15
10
5
0
Power
0
5
10
15
Frequency (Hz)
5% MVC
50% MVC
75% MVC
Noise

b)



1
0.8
0.6
0.4
0.2
0
Power
15
20
25
30
Frequency (Hz)
50% MVC
75% MVC
Noise

Figure 3

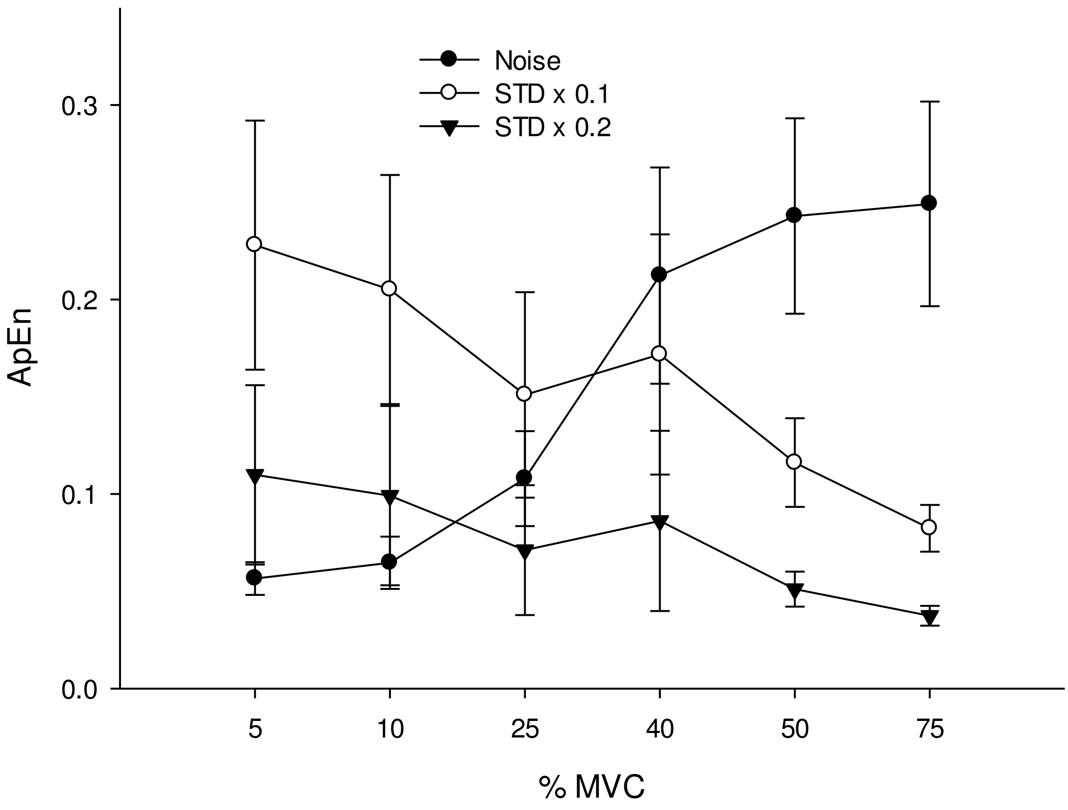


Figure 4

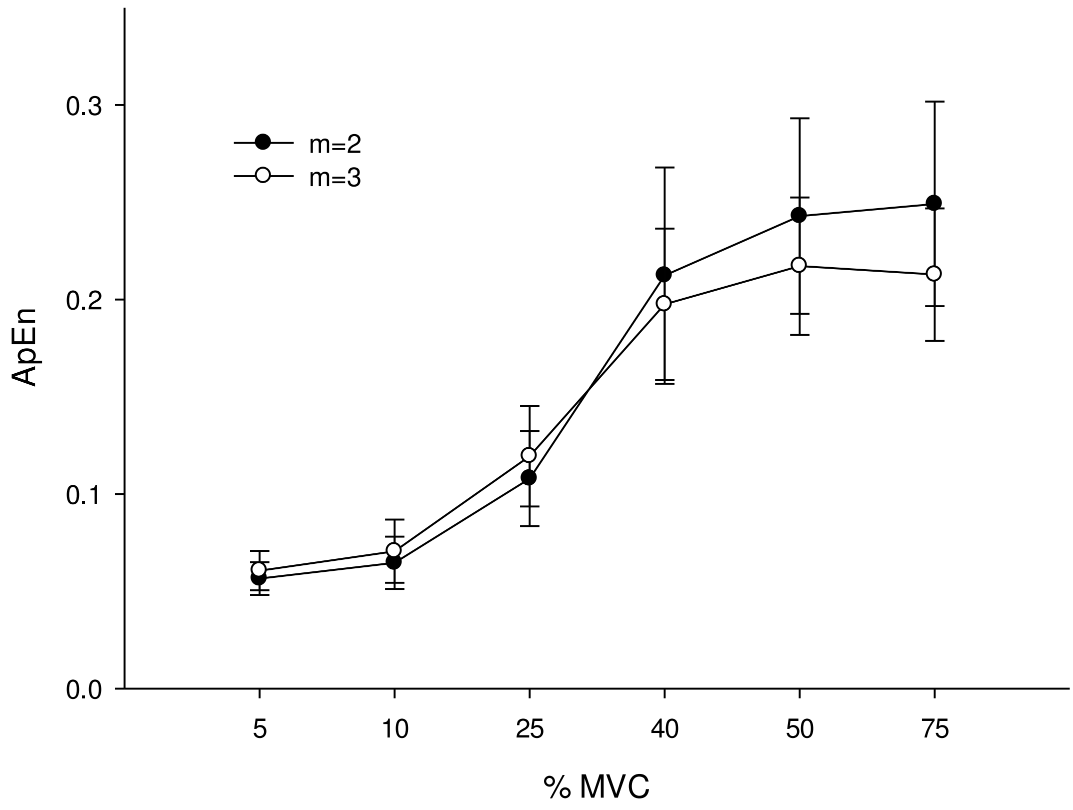


Figure 5

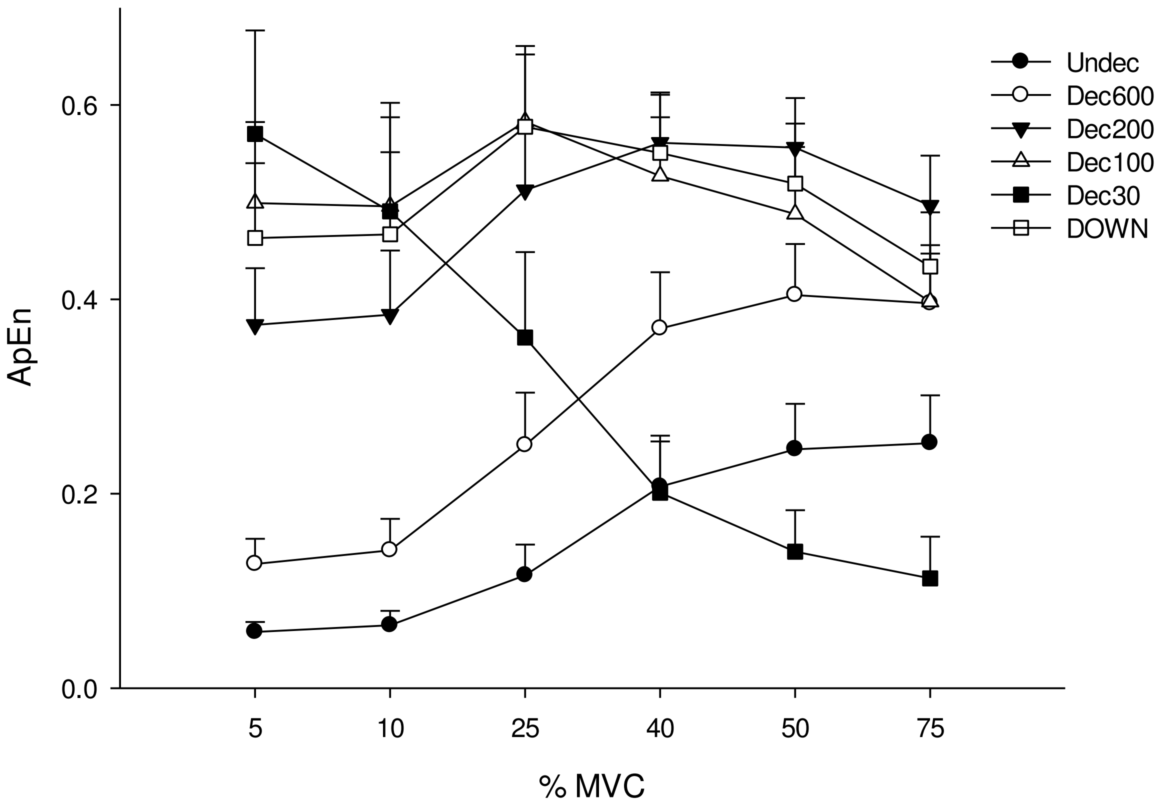

ApEn
0.0
0.2
0.4
0.6
5
10
25
40
50
75
% MVC
Undec
Dec600
Dec200
Dec100
Dec30
DOWN

Figure 6

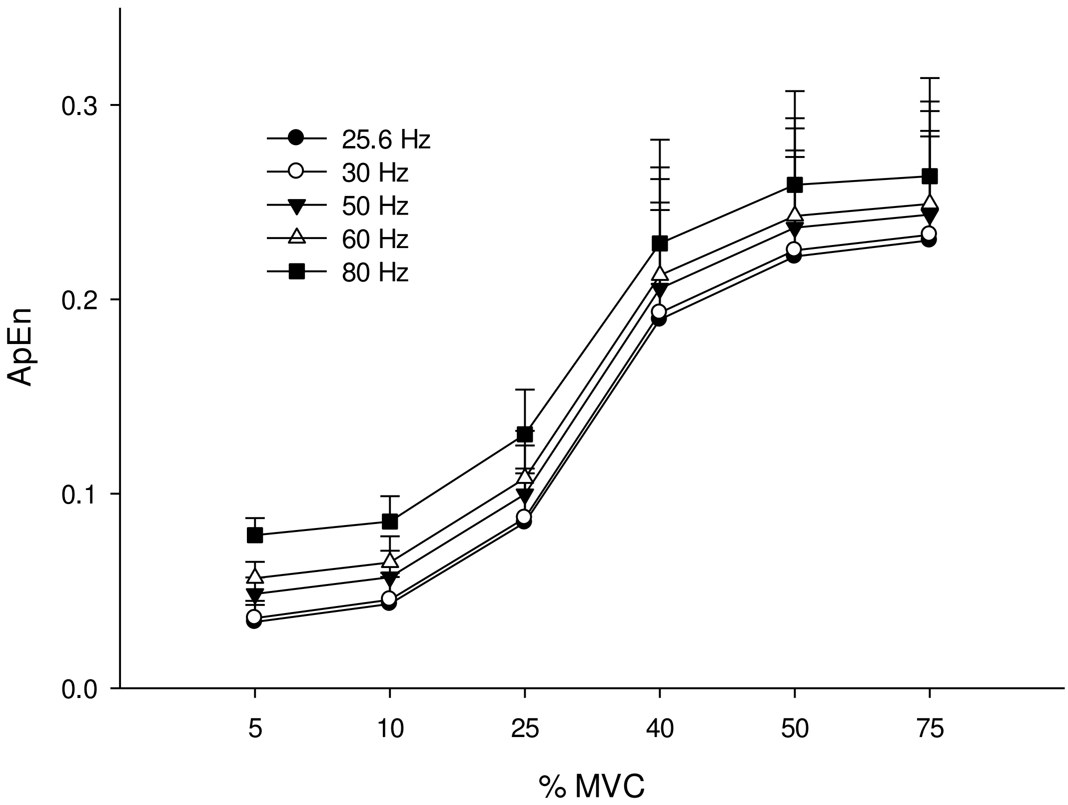
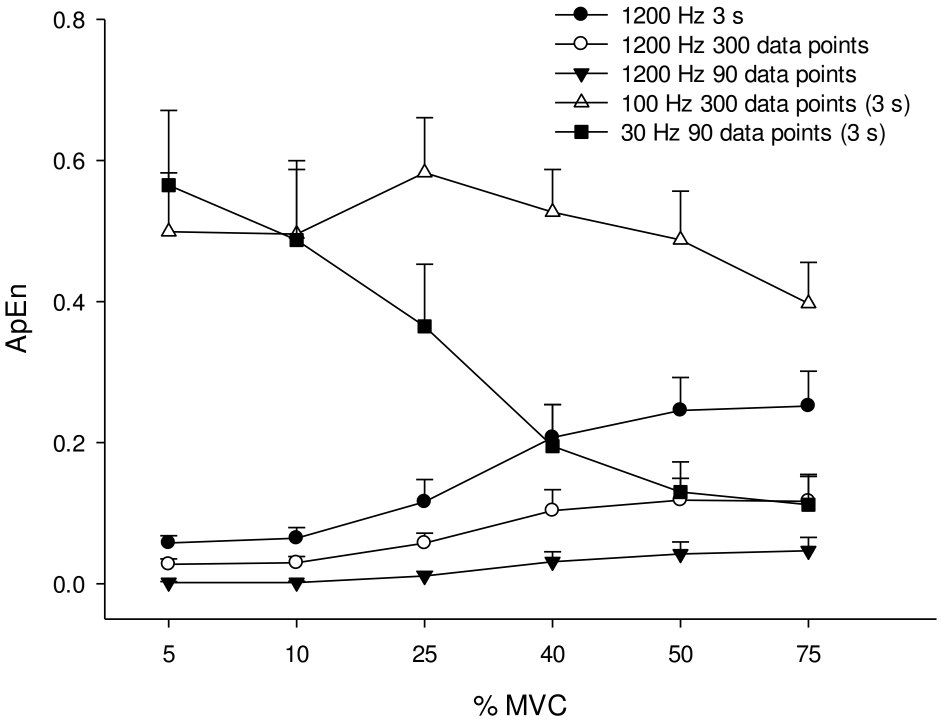


Figure 7

a)


1200 Hz 3 s
1200 Hz 300 data points
1200 Hz 90 data points
100 Hz 300 data points (3 s)
30 Hz 90 data points (3 s)
ApEn
0.8
0.6
0.4
0.2
0.0
5
10
25
40
50
75
% MVC

b)

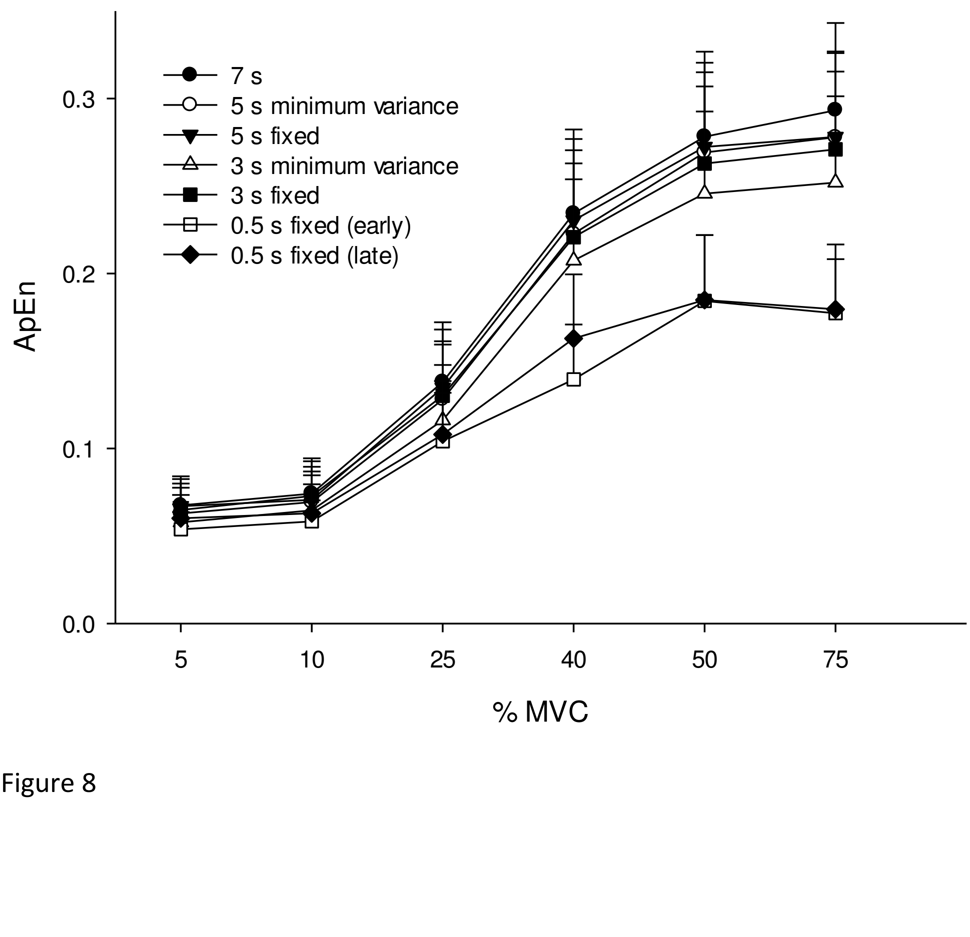

7 s
5 s minimum variance
5 s fixed
3 s minimum variance
3 s fixed
0.5 s fixed (early)
0.5 s fixed (late)
ApEn
0.3
0.2
0.1
0.0
5
10
25
40
50
75
% MVC

Figure 8