The size and structure of forces variability differ during short, ramp and sustained contraction in males and females

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Abstract

The aim of this study was to investigate the effect of gender differences on 3D force variability assessed by means of linear and nonlinear methods during short duration, ramp and sustained isometric elbow flexions.

Ten males and 10 females performed elbow flexion receiving visual feedback from the direction of force exertion. Elbow flexions were performed at (1) maximum voluntary contraction (MVC), (2) at10-90 %MVC with 10 % increment for 5 s, (3) at 5-50 %MVC (30 s ramp), (4) at 20%MVC until task failure and, (5) MVC. Standard deviation (SD), coefficient of variations (CV) and sample entropy (SaEn) were computed from the force signals recorded in 3D. SD, CV and SaEn changed with increasing force level and contraction time in 3D ($p < 0.01$). SD, CV and SaEn were higher in males than females ($p < 0.05$). SD increased with contraction level up to 100% MVC while SaEn changed according to an inverted U-shape function ($p < 0.01$). SD and CV increased with contraction time ($p < 0.01$).

Separate control mechanisms could be responsible for the observed changes in force variability with increasing contraction level and with contraction time. The absolute differences in standard deviation, coefficient of variations and sample entropy during short and sustained isometric contractions point towards possible gender-dependent force control mechanisms.

Introduction

Studying gender differences with respect to e.g. pain and motor control has attracted a lot of interest within the last decade [Greenspan et al. 2007, Semmler al. 1999]. Among these differences is a greater absolute force developed by males compared with females [Miller et al. 1993]. In parallel, females are more fatigue-resistant than males during relative endurance tasks at sub-maximal force level [Maughan et al. 1986, Semmler et al. 1999]. Such differences have been shown for several muscle groups, including e.g. elbow flexors [Kahn et al. 1986, Sato and Hohashi 1989].

Differences in factors like muscle mass, muscle morphology, substrate utilization and neuromuscular activation in muscle most likely count for gender differences in fatigue development [Sejersted et al. 1984, Hicks et al. 2001, Krogh-Lund and Jørgensen 1991].

For larger strength, a larger muscle mass is essential. That could result in larger increased intramuscular pressure among males compared with females due to a larger absolute force necessary to carry out the same sub-maximal force level. Thus, metabolic imbalance between supply and demand may occur, resulting in a greater rate of fatigue development in males [Béliveau et al. 1992, Sahlin et al. 1992].

Contradictory results are reported in studies testing gender difference in strength matched groups: No difference between genders is found in line with the hypothesis that intramuscular pressure and muscle mass play a role [Hunter and Enoka 2001, Clark et al. 2003], while another study from the same group

has shown opposite results arguing for a less potent effect of metabolic imbalance [Hunter et al. 2004].
The influence of muscle composition on gender differences is not yet elucidated. Miller et al. (1993) showed for the biceps brachii muscle that males have almost twice the size of type 2 fibers but the same area of type 1 fibers compared with females, while muscle fiber distribution is similar among genders [Manta et al. 1995].
In addition to muscle composition, neuromuscular activation and coordination have been suggested as important factors but only a few studies have examined this issue [Beck et al. 2005, Ge et al. 2005, Nie et al. 2007]. An altered neuromuscular activity is reported to lead to improved recovery period for the deactivated motor units during endurance contraction [Fallentin et al. 1993, Hunter and Enoka 2003], and this mechanism could be more potent for females compared with males explaining difference in a endurance task [Semmler et al. 2000, Larivière et al. 2006].

The recruitment of motor units is dependent on the required force output. This is defined as Hennemans size principle, which says that the level of recruitment of motor units depends on the force output. If a small output force is needed, the smallest motor units are recruited and for a large force output larger and more superficial motor units are recruited [Henneman 1985]. Thus, the recruitment order is that small fatigue-resistant motor units are recruited first and then the larger motor units are activated. A study has shown that the biceps brachii recruits additional units up to about 90% MVC [Kukulka and Clamann 1981].

Fluctuation in a signal recorded is in general perceived as noise and disturbance to the signal of interest. In studies investigating force control, force fluctuation or variability can be a way to assess aspect of the motor control. As previous studies have indicated, variability is not random like noise, but exhibit a degree of order that can be attributed to the operation of an adaptive control system [Slifkin and Newell 1999]. The magnitude of variability is capture by linear methods applied the time series, but to analyze the nonlinear structure and behavior of the time series, nonlinear methods provide important further information [Pincus 1991, Slifkin and Newell 1999]. Nonlinear methods are derived from chaos theory and have developed to be useful approach in the analysis of physiological signals [Richman and Moorman 2000, Slifkin and Newell 1999]. The structure of variability is usually measured by computing the approximate or sample entropy of the force signal. However, none of the studies investigating force variability have recorded the exerted force in more than one dimension. Moreover, only linear methods have been used to assess variability in genders during e.g. sustained contraction [Hunter and Enoka 2001] calling for further studies describing the structural changes of 3D force variability in relation to gender difference.

The purpose of this study was to examine the effect of gender differences on 3D force variability assessed by means of linear and nonlinear methods during short duration, ramp and sustained isometric elbow flexions.

Materials and methods

Subjects

Ten males and 10 females participated in the study. The subjects' anthropometric information can be seen in table 1. All subjects were healthy and without any known neurological disorders. All procedures in the experiment were conducted in accordance with the Declaration of Helsinki and informed consent was obtained from all participants.

	Females	**Males**
Age (years)	24.7 ± 3.9	25.8 ± 2.5
Weight (kg)	65.8 ± 9.3	80.2 ± 7.0
Height (cm)	170 ± 7.7	188.9 ± 7.2
Body Mass Index (BMI)	22.6 ± 2.4	22.5 ± 1.2

Table 1: Groups characteristics (mean ± SD).

Experimental procedure

Force development and maintenance from the dominant arm were investigated. For this purpose the subjects performed isometric elbow flexions at various contraction levels of different duration. The forces developed during elbow flexion were recorded in 3D. During the recordings, subjects were sitting on a chair and holding the force sensor with the palm towards the ceiling and the elbow flexed at 90 degrees (figure 1). The arm was in contact with the chest (slight touch). This position was controlled by the experimenter throughout the experiment.

The experiment consisted of 5 contraction trials:

1. Initial maximal voluntary contraction (MVC_{int})
2. Short duration contractions
3. Ramp contraction
4. Endurance contraction
5. Final MVC_{final}

MVCs during elbow flexion were recorded three times to determine strength of each subject. Each trial lasted 3 seconds and was separated by 2 minutes. MVC_{init} was used as reference contraction to set various sub-maximal levels and to measure muscle fatigue after endurance test (MVC_{final}). Verbal encouragement was given during MVC and endurance test.

For the short duration contractions, ramp and endurance contraction force developed during the elbow flexion was visually fed back to the subjects continuously.

The short duration contractions consisted of nine contractions from 10% to 90% of MVC_{init} with a 10% increment in between. The order of the contractions was random to prevent a priori knowledge of the following contraction level. Each of the contractions lasted 5 seconds with a break of approximate 30 seconds in between.

The ramp contraction lasted 30 seconds starting at 5% and reaching 50% MVC_{init} (slope of 1.5 %MVC/s).

For the endurance contraction the subjects had to maintain a 20% MVC_{init} level until task failure. Task failure occurred when the subjects were not able to maintain force at 20 ± 2%MVC for more than 5 seconds.

Thirty seconds after the endurance test, MVC_{final} was recorded.

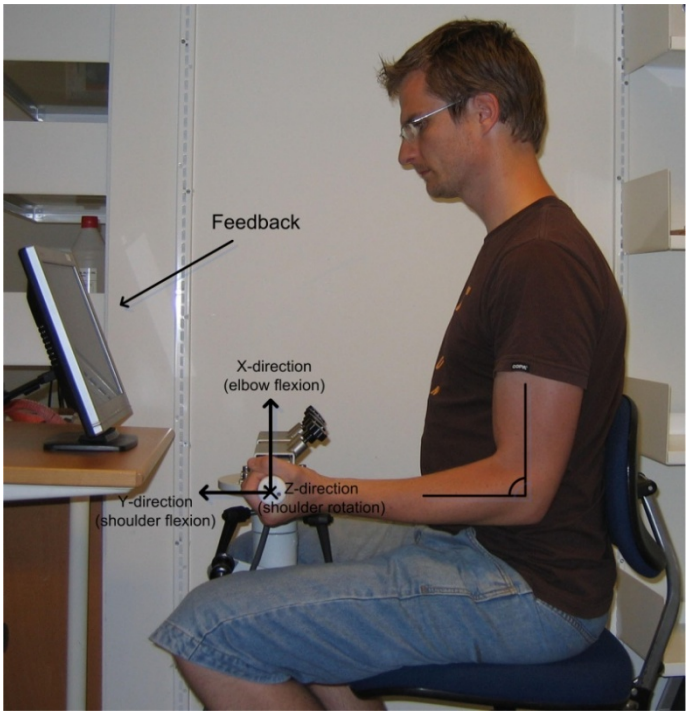

Figure 1: Experimental setup with the force directions shown.

Data analysis

Forces were measured in 3D by means of a force sensor (FS-6, AMTI, Watertown, Massachusetts, USA). The x-, y, and z- directions recorded respectively elbow flexion, shoulder flexion and rotation. Force signals were low-pass filtered (10.5 Hz) and amplified 1000 times. The signals were AD-converted (12 bits A/D converter, Nidaq 6024, National Instruments, Austin, Texas, USA) and recorded through a custom made program in Labview 8.2 (National Instruments, Austin, Texas, USA), which also provided force feedback to the subject. All signals were sampled at 500 Hz and saved for further analysis in MATLAB R2007a (The MathWorks Inc, Natick, Massachusetts, USA).

MVC were computed over 1 second with 0.1 second overlapping. The highest force was then considered as MVC.

Linear analysis of the force signals was performed to quantify the amount of variability. Standard deviation (SD) and coefficient of variation (CV) were calculated. SD reflects the size of the variability, and CV is the relative variability. CV was derived from mean and SD of the signal and calculated as below:

$$CV = \frac{SD}{mean}$$

Nonlinear analysis of the force signals was also performed to examine the structure of variability. Sample entropy (SaEn) was computed for this purpose [Richman and Moorman, 2000]. SaEn expresses the complexity of the recorded signal [Kuusela et al. 2002].

When SaEn is calculated an embedding dimension m and a tolerance level r has to be chosen. In this study, the embedding dimension m was set to 2 and the tolerance level r to 20% of the standard deviation of the signal. From the embedding dimension the state space can be constructed, which is the space from where the nonlinear methods are derived. The time series *x(n)* of length N is divided into *N-m+1* vectors of the state space. The vectors are defined as:

$$u(i) = [x(i), x(i+1), \dots, x(i+m-1)],$$
$$1 < i < N - m + 1$$

The distance between each vector in the state space is now calculated by the distance equation of maximum absolute difference:

$$d[u(i), u(j)] = \max(|u(i,k) - u(j,k)|),$$

$$1 \leq k \leq m$$

with j counting *(1 ≤ j ≤ N − m, j ≠ i).* The number of *d[u(i), u(j)] < r* divided by *N-m+1* is defined as B_i^m for all *i* and:

$$B^m(r) = (N-m)^{-1} \sum_{i=1}^{N-m} B_i^m(r)$$

When B^m is calculated, the state space and distance matrix d is calculated again for embedding dimension m+1. From the new distance matrix, the number of *d[u(i), u(j)] < r* divided by *N-(m+1)+1* is defined as A_i^{m+1} for all *i* and:

$$A^{m+1}(r) = (N-(m+1))^{-1} \sum_{i=1}^{N-(m+1)} A_i^{m+1}(r)$$

Then the sample entropy (SaEn) for the time series of length N can be calculated as:

$$SaEn(m, r, N) = -\log\left(\frac{A^{m+1}}{B^m}\right)$$

SaEn is the negative logarithm of the relationship between the probability that two sequences coincide for m+1 and for m points.

For the short duration contractions, SD, CV and SaEn were calculated over 3 second epoch (discarding first and last second) for each contraction level. For the ramp contraction, linear and non-linear parameters were calculated over 3 second epochs through the contraction and while for the endurance contraction, seven (0 to 100% of contraction time by steps of 16.7%) epochs of 10 seconds were used.

Statistical analysis

A one-way analysis of variance (ANOVA) with factor gender and dependent variable: endurance time, a 2-way ANOVA with factors gender and time (before/after endurance test) and dependent variable: MVC level and a 3-way ANOVA with factors gender, contraction level/contraction time and force direction and dependent variables: SD, CV and SaEn were performed using SPSS 16.0 (SPSS Inc., City, USA) A post-hoc test of Least Significant Difference was used for pair wise comparisons. Mean ± SD is reported. The level of significance was set at $P < 0.05$.

Results

The 2-way ANOVA revealed that males had higher MVC than females (F=70.9, p<0.01) and a force drop between MVC_{init} and MVC_{final} (F=11.5, p<0.01). The MVC results are shown in table 2.

MVC(N)	MVC_{init}	MVC_{final}
Females	152.5 ± 18.4	116.9 ± 19.1 †
Males	272.9 ± 61.9	219.0 ± 49.5

Table 2: Mean ± SD for males and females prior MVC_{init} and after MVC_{final} the endurance contraction. † significant difference among respectively gender and MVC_{init} and MVC_{final}.

Short duration contractions

Table 3 shows the results of the 3-way ANOVA. Significant gender difference between genders towards high contraction level for both SD and CV (see figure 2). SD increased with contraction level with larger SD for males compared with females for all force contractions. CV in the y-direction was larger for females compared with males.

SaEn increased up to approximately 40% MVC and then decreased towards the higher contraction levels. This progress only exists for the x-direction where gender differences were present at 40% MVC (higher values for males compared with females).

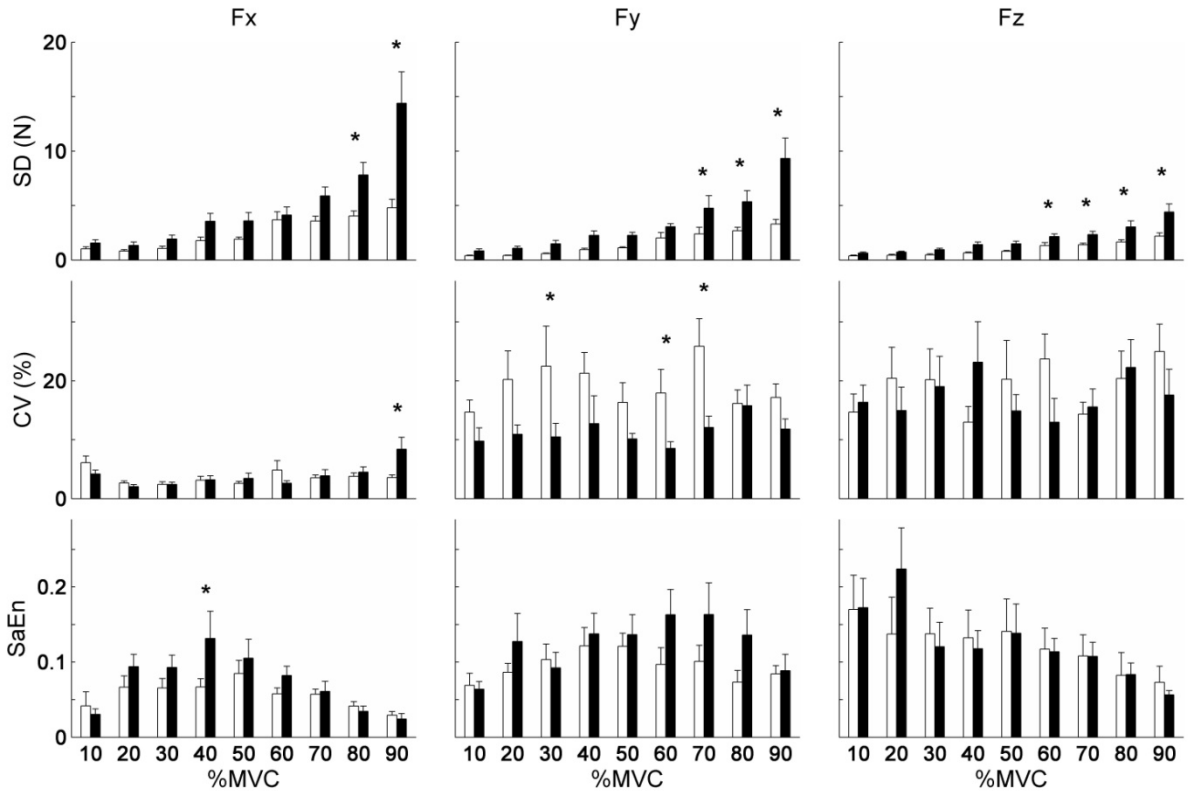

Figure 2: Mean + SE of SD, CV and SaEn for force in the x- (elbow flexion), y- (shoulder flexion) and z-direction (rotation) as a function of contraction level. White bars are females and black are males. * marks significant difference between genders.

Ramp contraction

Table 3 shows the results of the 3-way ANOVA. Like for the short duration contractions, SD, CV and SaEn computed during the ramp contraction depended of contraction level. Figure 3 shows the variability measures for all contraction levels and force directions.

SD increased with increasing contraction level and was larger for males compared with females while the opposite occurred for CV.

SaEn increased with increasing contraction levels and was larger for males compared with females.

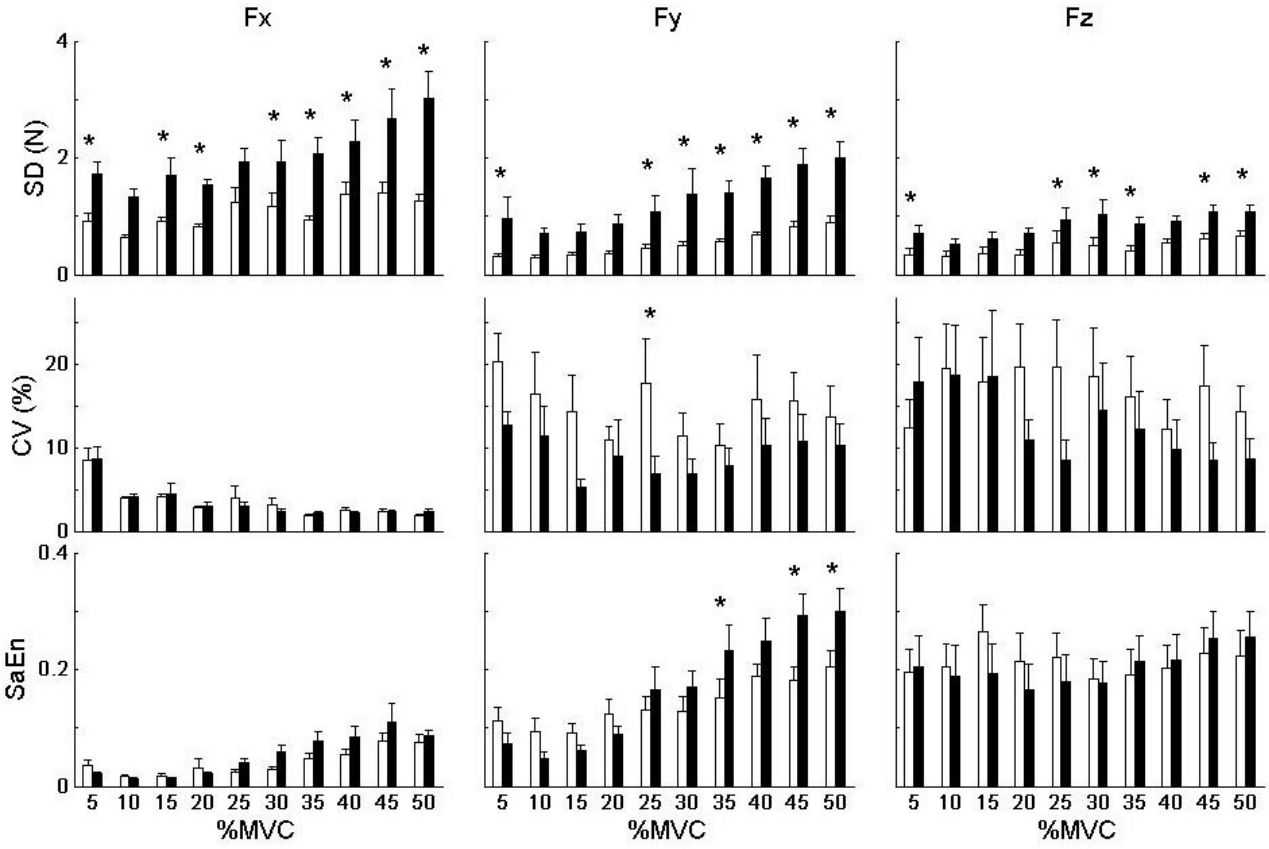

Figure 3: Mean + SE of SD, CV and SaEn for force in the x- (elbow flexion), y- (shoulder flexion) and z-direction (rotation) as a function of contraction level. White bars are females and black are males. * marks significant difference between genders.

Endurance contraction

Table 3 shows the results of the 3-way ANOVA. Females had longer endurance duration compared with males, respectively 682.8 vs. 344.8 seconds ($F = 7.5$, $p = 0.01$).

Both SD and CV increased with contraction time with higher SD for males compared with females present at all time.

SaEn increased with contraction time in the x- and y- direction. In figure 4 the variability measures are shown for the endurance contraction.

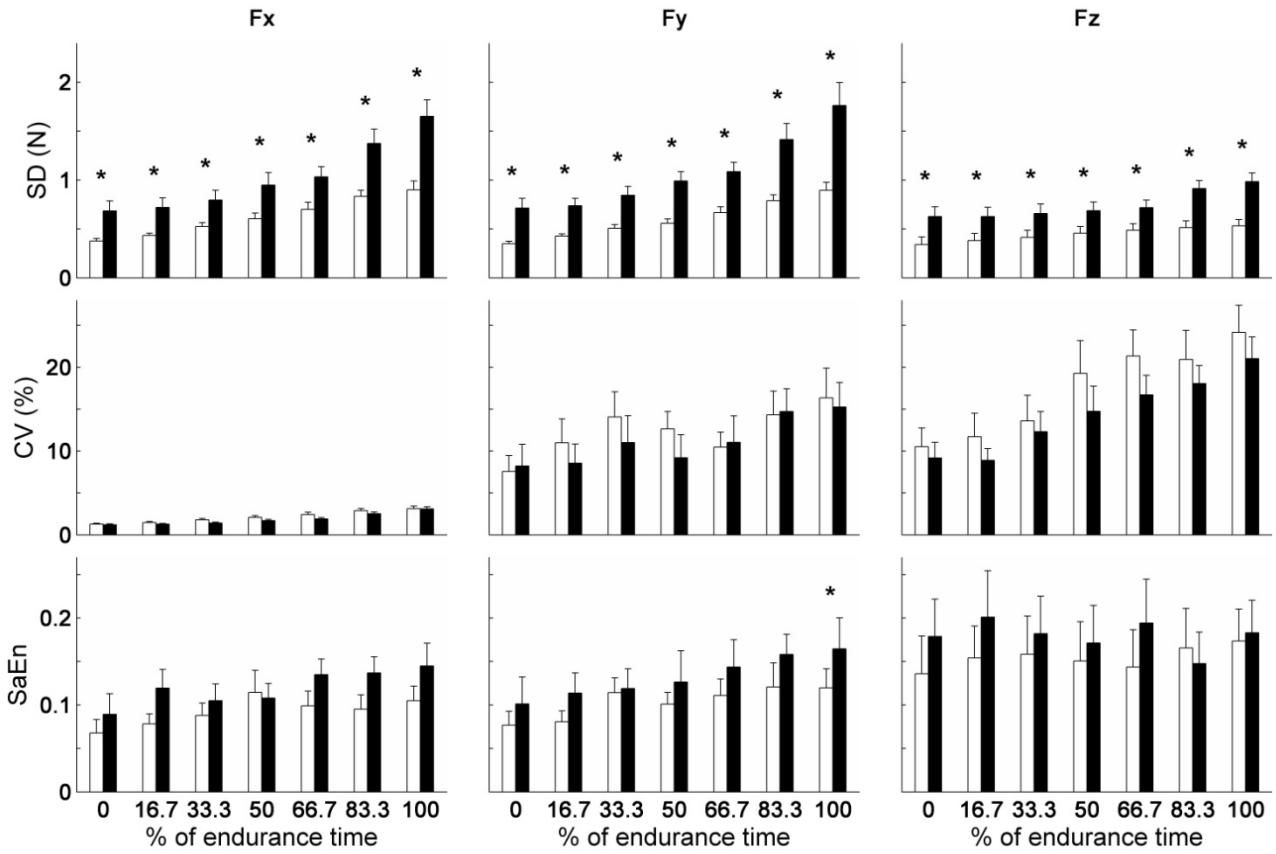

Figure 4: Mean + SE of SD, CV and SaEn for force in the x- (elbow flexion), y- (shoulder flexion) and z-direction (rotation) as a function of contraction time. White bars are females and black are males. * marks significant difference between genders.

	SD		CV		SaEn	
	F	p	F	p	F	P
Short contractions						
- Gender (G)	92.97	**<0.01***	12.11	**<0.01***	5.24	**0.02***
- Contraction level (CL)	48.71	**<0.01***	0.62	0.77	4.15	**<0.01***
- Force direction (FD)	54.50	**<0.01***	100.55	**<0.01***	25.92	**<0.01***
- G×CL	10.84	**<0.01***	1.00	0.44	0.77	0.63
- G×FD	6.31	**<0.01***	7.47	**<0.01***	0.98	0.38
- CL×FD	4.01	**<0.01***	0.74	0.75	1.92	**0.02***
- G×CL×FD	1.64	**0.05***	0.92	0.54	0.57	0.91
Ramp contraction						
- Gender (G)	217.42	**<0.01***	26.24	**<0.01***	12.62	**<0.01***
- Contraction level (CL)	15.85	**<0.01***	3.39	**<0.01***	31.18	**<0.01***
- Force direction (FD)	61.20	**<0.01***	61.09	**<0.01***	136.70	**<0.01***
- G×CL	2.52	**<0.01***	0.78	0.64	5.54	**<0.01***
- G×FD	1.60	0.20	6.46	**<0.01***	0.76	0.47
- CL×FD	0.16	1.00	0.31	0.99	1.99	**0.01***
- G×CL×FD	0.18	1.00	0.15	1.00	0.62	0.89
Endurance contraction						
- Gender (G)	186.21	**<0.01***	4.54	**0.03***	8.18	**<0.01***
- Time (T)	34.10	**<0.01***	8.47	**<0.01***	1.01	0.42
- Force direction (FD)	30.03	**<0.01***	141.13	**<0.01***	15.48	**<0.01***
- G×T	4.07	**<0.01***	0.18	0.98	0.19	0.98
- G×FD	3.31	**0.04***	1.28	0.28	0.01	0.99
- T×FD	2.47	**<0.01***	2.18	**0.01***	0.27	0.99
- G×T×FD	0.24	0.99	0.16	1.00	0.19	0.99

Table 3: All statistical results for the 3-way ANOVAs of the 3 contraction types, short contractions, ramp contraction and endurance contraction. * is significant p-values.

Discussion

The present study aimed at investigating the effects of gender on force variability measured in 3D by means of linear (variability size) and nonlinear (variability structure) analysis during voluntary short duration, ramp and sustained isometric elbow flexions. The findings revealed for the first time that in short, ramp and sustained contractions: (i) the size and the structure of the force during voluntary contraction were not only affected in the direction of force exertion (elbow flexion) but also in the other two directions (shoulder flexion and rotation), (ii) gender played a role in force variability, females being usually characterized by lower amount (SD) and structural complexity (SaEn) than males, (iii) the size of variability increased with contraction level up to 100% MVC while the structure of variability changed according to an inverted U-shape function, (iv) the size of variability increased with contraction time.

Methodological considerations regarding variability assessment methods

Standard deviation, variance and coefficient of variation measures have been widely used for assessing motor variability due to their simplicity [Madeleine et al. 2008]. To quantify the amount of variability present in the force signals, SD and CV

were used. CV shows intra-subject variability and changes in variability. But for inter-subjects comparison, the use of SD can be questionable, since comparison of SD from subjects with different absolute force can be difficult to interpret as the variability arises from different amounts of absolute force [Newell and Corcos 1993]. This is one of the reasons CV has been calculated in this study, as well. CV is SD relative to the force level and the variability is normalized to be fluctuation in the signal as a percentage of mean.

However, nonlinear analysis is required for analyzing motor control strategies in depth [Sosnoff et al. 2006]. These methods include e.g. approximate or sample entropy, correlation dimension, fractal dimension and Liv-Zempel entropy [Kuusela et al. 2002]. Sample entropy was chosen to describe changes in force signal complexity and preferred to approximate entropy as it excludes self-matches [Richman and Moorman 2000]. For the calculation of sample entropy the embedding dimension and tolerance level have to be set. According to previous studies [Richman and Moorman 2000, Kuusela et al. 2002], m was set to 2 and r was set to 20% of the standard deviation of the force signal to enable a confident estimation of the sample entropy. Likewise, the epoch length of the signal to calculate sample entropy was given. The use of a fixed embedding dimension can be questioned [Lake et al. 2002] and other studies have suggested using a technique of calculating false nearest neighbors [Hegger and Kantz 1999, Nichols and Nichols 2001], since it can give the true value of the embedding dimension and finally the clearest result. If the embedding dimension is not set to fit the deterministic signal, then the result can reflect some sort of randomness, as the embedding dimension is given as the number of dimensions needed to unfold the structure of the system or signal [Stergiou et al. 2004]. However, the choice of a fixed embedding dimension and tolerance level is sounded for group comparison purpose of sample entropy values but one should be careful as the sample entropy values obtained depend on embedding dimension, tolerance level, sample frequency and sample length.

Effect of force direction on force variability

Studies assessing gender difference and force variability have generally focused on mono-directional force exertion omitting to consider possible changes in direction during force exertion. The present study considered this aspect as forces were measured in 3D enabling to assess changes in the two other directions. The type of isometric contraction performed consisted of elbow flexion. Moreover, visual feedback was only given in the elbow flexor direction. However, the size and the structure of the force during voluntary contraction changed also in shoulder flexion and rotation directions. The analysis of force in several directions for elbow flexion could give an enhanced insight to the coordination of muscles and recruitment of motor units. But such studies combining 3D force sensors and muscles activity assessment have not previously been conducted for the biceps brachii. The observed changes in the size and structure of variability occurring in 3D even during mono-directional movement can be explained by a lack of control of the subjects' dominant arm position as the actual arm position was solely controlled by the experimenter and/or most likely compensatory mechanisms like co-contraction and changed agonist/antagonist relationship aiming at maintaining the same force output during sustained contraction [Ervhila et al. 2004, Rudroff et al. 2008]. The present results argue for the use 3D force assessment for a full interpretation of changes in force variability during increasing level and sustained contractions.

Effect of contraction level and gender on force variability

For the short duration contractions with increasing contraction levels and ramp contraction, the observed changes in the size and structure of variability are in line with previous results [Slifkin and Newell 1999]. SD has been reported to increase exponentially while CV decreased. In the short contractions, CV remained low during elbow flexion, this could be due to failure in reaching the required level of contraction at high sub-maximal

contraction levels. In the ramp contraction on the other hand, CV decreased. This development of the variability measures was present for both males and females, but SD in the elbow flexion showed significant difference between genders throughout MVC levels, with males showing larger SD than females. For CV, the result was opposite. Gender differences at different contraction levels were expressed by larger amount of variability (SD) for males compared with females and this result could indicate that males have a elevated activity in the biceps brachii muscle compared with females due to higher absolute force level [Hunter and Enoka 2001] and that muscle activation pattern are different among genders [Ge et al. 2005, Yoon et al. 2007]. A hypothesis regarding change in variability with increasing contraction level is that the variability would also increase. In this study, SD increased exponentially (Figure 2) as it has also been reported earlier [Slifkin and Newell 1999, Tracy et al. 2007], but the variability relative to the force level (i.e. CV) at the different contraction levels did not change while during ramp contraction CV decreased slightly with increasing contraction level. This can be expected as SD increased exponentially with force increasing while the force increase was linear resulting in a decreasing CV as shown earlier [Sosnoff et al. 2006].

For the structure of the variability, my result also agrees with the results found by Slifkin and Newell (1999). SaEn increased up to approximate 40% MVC and then decreased. The inverted U-shape of variability structure in the force signal has previously been shown [Slifkin and Newell 1999]. The complexity of the force signal was also higher in males compared with females arguing again for gender depend force control strategies.

These findings suggest that the recruitment of new motor unit during short duration and ramp contraction does not affect the structure of force variability. Thus, the present study confirm and expand to the whole contraction range that the size and structure of force variability could be governed by separate control processes as proposed by Sosnoff et al. (2006).

Effect of endurance time and gender on force variability

The endurance time in the study confirmed difference between genders as reported earlier [Maughan et al. 1986, Hunter et al. 2001, Sato and Ohashi 1989]. The amount and structure of force variability increased slightly during the endurance contraction but not significant. For SD a general gender difference occurred throughout the entire contraction, as SD for males was larger compared with females in all force directions. CV showed as expected, the opposite result with females having larger values than males (see methodological considerations). The results concerning gender effects on CV agrees with a recent result from Yoon et al. (2007). The sample entropy differed also between genders, with males having higher force signal complexity than females similar to the difference observed during increasing force level.

Muscle fatigue is found to alter biomechanical movement patterns [Gates and Dingwell 2008]. Beside fatigue effects on force variability, the present gender-dependency in the amount and structure of force variability could be due to discrepancies in muscle activation pattern among genders [Ge et al. 2005, Yoon et al. 2007]. During an intermittent fatiguing task, males are reported to require a greater rate of descending drive to maintain the requested force level compared with females [Hunter et al. 2004]. Moreover, an increased accumulation of metabolites in the males' muscle compared with females' most likely resulted in an increased afferent feedback to spinal and supraspinal centers [Gandevia 2001]. This in turn will influence maximum voluntary activation after the endurance task (see Table 2). Fatigue was similar for males and females in line with Yoon et al. (2007) but the males are reported to fatigue more than the females because females experience less peripheral fatigue [Hunter et al. 2006]. All in all, these differences could account for the difference in size and structure of force variability observed in males during an

endurance contraction. Contrary to what was observed during short duration or ramp contractions, the control mechanisms influencing the size and structure of force variability during sustained contraction could be unified to sustain the desired force level.

Conclusion

In summary, the analysis of force variability in 3D showed for the first time that the amount and structure of force variability (i) changed in 3D even during mono-directional force exertion, (ii) was higher in males compared with females arguing for gender-dependent force control mechanisms. Moreover, the changes in the size and structure of force variability differed with increasing contraction level and increased similarly with contraction time. This could be due to separate control processes influencing force variability during short and sustained isometric contractions.

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Gender differences in force variability given by linear and nonlinear methods

Worksheets

Master thesis by

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The current **Master thesis** (article and worksheets) is submitted as a fulfillment of the requirements for the degree Master of Science in Biomedical Engineering and Informatics, at the Department of Health Science and Technology, Aalborg University, June 2008.
The aim was to investigate the effect of gender differences on 3D force variability assessed by means of linear and nonlinear methods during short duration, ramp and sustained isometric elbow flexions. Ten males and 10 females performed elbow flexion receiving visual feedback from the direction of force exertion. Elbow flexions were performed at (1) maximum voluntary contraction (MVC), (2) at10-90 %MVC with 10% increment for 5 s, (3) at 5-50%MVC (30 s ramp), (4) at 20%MVC until task failure and, (5) MVC. Standard deviation, coefficient of variations, approximate entropy and sample entropy were computed from the force signals recorded in 3D. SD, CV and SaEn changed with increasing force level and contraction time in 3D. SD, CV, ApEn and SaEn were higher in males than females. SD increased with contraction level up to 100% MVC while ApEn and SaEn changed according to an inverted U-shape function.
Separate control mechanisms could be responsible for the observed changes in force variability with increasing contraction level and with contraction time. The absolute differences in standard deviation, coefficient of variations and sample entropy during short and sustained isometric contractions point towards possible gender-dependent force control mechanisms.

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Preface

This collection of worksheets is submitted as fulfillment of the requirement for the degree Master of Science in Biomedical Engineering and Informatics. The worksheets are written by group 1088b at the Department of Health Science and Technology, Aalborg University, Denmark, during the 10^{th} semester on the Medical Systems and signals (MSS) specialty in the period February 1^{st} to June 2^{nd} 2008. The worksheets support the article entitled "*The size and structure of forces variability differ during short, ramp and sustained contraction in males and females*", and both productions are addressed to fellow students at the Department of Health Science and Technology, the project supervisor and other interested in analyzing force variability.

Readers guide:
The worksheets are written as more or less independent documents and need not to be read in any particular order. The main purpose of the worksheets is documentation of knowledge used in the project. At the end of the worksheets a bibliography is available for all worksheets. A CD-ROM containing the MATLAB code used throughout the project is enclosed.

Aalborg University, June 2008

Jacob Handberg Svendsen

Contents

Chapter 1

Analysis

In this chapter the difference in motor control between genders will be described. Previous findings will be used to set up the thesis for the study and a problem statement is presented at the end.

1.1 Difference between genders

The maximum force output performed voluntary differs between gender and between ages. This has been examined in several studies and it is a general perception that males are stronger than females and elderly have reduced voluntary maximal force compared to younger adults [Sosnoff and Newell, 2006]. By doing a maximal voluntary contraction (MVC) males in general can perform a force considerable larger than females due to the larger muscle mass [Maughan et al., 1986; Miller et al., 1993].

1.1.1 Endurance

As well as the MVC, the endurance time for a contraction going towards exhaustion and fatigue in the muscle, is age and gender related. Several studies have shown that older people have longer endurance time than younger adults for a contraction task of the same level of MVC when the level of the contraction is low (below 50 % of MVC) [Maughan et al., 1986]. Young adults can perform a higher MVC, but older adults have a slower development of fatigue in the muscles which lead to task failure [Yassierli et al., 2007]. For the difference between gender in endurance time and the reach of task failure, the main cause is not determined. Some of the suggestions to the difference are:

- Difference in neuromuscular recruitment strategy
- Distribution of different muscle fibers
- Intramuscular pressure, imbalance between blood supply and demand (muscle perfusion)
- Muscle temperature

A sub-maximal endurance task has in several studies shown that females have significant longer endurance than males and the motor unit recruitment strategy has been suggested as one reason of this difference between genders. [Semmler et al., 1999] The amount of motor units activated during a prolonged sub-maximal contraction going towards fatigue is in the same range for males and females [Hunter and Enoka, 2001], but for persons with longer endurance time, an altered level and different motor unit activation is present [Hunter and Enoka, 2003]. The firing and

characteristic of the motor units are influenced by the conduction velocity and the firing rate. These parameters could have an impact on the gender difference. Conduction velocity in general changes during a prolonged isometric contraction due to fatiguing units and recruitment of new ones [Houtman et al., 2003; Nordstrom and Miles, 1991]. The firing rate increases during the prolonged contraction as the demand of keeping the contraction level proceeds during the prolonged contraction.
For a sub-maximal contraction relative to MVC males usually have to produce higher force to keep the same sub-maximal level, compared to women, who produce less force for the MVC. With greater force output for males, the activated motor units fatigue more rapidly and additional units have to be recruited. Due to a higher firing rate motor units tend to fatigue more rapidly than motor units supplied with lower firing rate [Bigland-Ritchie et al., 1983]
As another form of neuromuscular recruitment strategy, the activation of synergist muscles can be have an influence on the difference between genders. The activation of synergist has shown to attenuate muscle fatigue [Kouzaki and Shinohara, 2006] and could be a useful to prolong the endurance.
The distribution of muscle fibers differs between gender and it is reported that males have a larger ratio of type II fibers compared to type I. [Miller et al., 1993] This could give the advantage of a better performance for females in an endurance contraction.
Due to a larger muscle mass males can generate larger force that females, but it has been hypothesized that when performing a sub-maximal contraction, the larger muscle mass can result in a higher intramuscular pressure, which can lead to a reduced muscle perfusion. An increased intramuscular pressure and a reduced muscle perfusion can cause imbalance between the blood supply to the muscle and the demand during a task going to fatigue [Sejersted et al., 1983].

The performance of muscles vary with temperature and this could have an effect on the endurance since females have more subcutaneous adipose tissue than males, which could lead to a slightly higher muscle temperature in females. But temperature is not generally thought to vary with gender [Clark et al., 2003].

1.1.2 Recruitment order

The recruitment of motor units is dependent on the required force output. This is defined as Hennemans size principle, which says that the level of recruitment of motor units depends on the force output. If a small output force is needed, the smallest motor units are recruited and for a large force output larger and more superficial motor units are recruited [Henneman, 1985]. Thus, the recruitment order is that small fatigue-resistant motor units are recruited first and then the larger motor units are activated. A study has show that the biceps brachii recruits additional units up to about 90% MVC [Kukulka and Clamann, 1981].

1.1.3 Summary

Several suggestions to the differences in endurance between genders have been stated above. The proposal of the difference in intramuscular pressure is reasonable, but in a recent study, Hunter and Enoka [2003] demonstrated that no difference was present in blood supply to the muscle for performances of long and short endurance time. The intramuscular pressure had no influence as the fluid pressure increased. The muscle activation on the other hand seemed to differ and thereby was altered and a different activation pattern for the motor units was present. Likewise, the difference in distribution of muscle fibers is relevant and the activation of synergist. The Activation pattern and the muscle fiber distribution are connected as the activation pattern of

type I and type II fibers are different.

1.2 Noise or variability?

The perception of fluctuation in a recorded signal is often characterized as noise. But it is important to determine the origin of this noise as it can carry useful information. For instrumental recordings, white noise can be present and this type of noise is defined as random fluctuation which has no information but noise. In recordings of force linear measures like standard deviation can show the variability of the force signal. The variability of the force signal is a deterministic fluctuating signal compared to the white noise.[Newell and Corcos, 1993] From information theory of human performance, the hypothesis is that the increase in force variability is related to increasing noise in the perceptual motor processes involved in force production [Fitts, 1954].
In a task where the output is related to at certain goal e.g. a force specified output, the motor response adapts rapidly, and dependent on the force level the output can be held for longer or shorter time. During a sustained sub-maximal contraction the motor response varies and the longer a contraction is held, the larger the variability. For tasks going towards fatigue, the force output will start to fluctuate more and more until task failure and the level of force can no longer be maintained. Variability in the motor response is due to coordination of the recruitment and as higher force is required, the variability increases. As the variability of the force increases for larger contraction amplitude, the structure of the variability evolves like an inverted U-shape [Slifkin and Newell, 1999]. The structure of the variability in the force task recording is calculated by nonlinear methods. Slifkin and Newell [1999] used the approximate entropy to show the structure. The linear and nonlinear measures give different information and can not only show the fluctuations in the motor control, but also the structure of the recruitment. Thus it is possible to study the motor control pattern by studying the force variability. [Newell and Corcos, 1993]

1.3 Force and variability

For previous recordings of force and variability in assessment of gender differences, two issues can be emphasized; recordings are generally made for one dimension and the force is only assessed by means of linear methods [Maughan et al., 1986; Hunter and Enoka, 2001; Garland et al., 1994]. As mentioned above, Slifkin and Newell [1999] used nonlinear methods to examine the structure of the variability in the force signal. This approach is indeed relevant in the comparing of genders as the structure. The other issue is the dimension. If additional dimension is used, the stability of the contraction can be assessed.

1.4 problem statement

The above of the issues of gender differences and analyzing motor control leads toward the problem statement: **How can the use of linear and nonlinear methods delineate gender differences with respect to force control and maintenance?**
How does one-direction force control and maintenance affect the other direction in genders?
To answer the problem statement, an experiment is being performed to show any differences between genders.

1.4.1 Study design

The purpose of this study is to examine gender differences in force and variability during sub-maximal contractions. To examine the force and variability an experiment is made for a sustained sub-maximal isometric contraction of the elbow flexor muscles. The force is recorded in 3 dimension, x, y, and z. When 3 dimensions are present, the variability in the main direction can be analyzed as done previously. But the stability of the contractions can likewise be observed. In the study several trials are performed to get different motor response patterns from the trials. The reference contraction in the experiment is MVC, recorded as the first contractions. From the MVC the levels of the other trials are set. Mainly three trials are of interest:

- Short contractions of levels going from 10% MVC to 90% MVC by steps of 10%
- Ramp contraction, 5-50% MVC with a slope of 1.5%/second
- Endurance contraction at 20% MVC

As the last of the three trials is an endurance contraction going to exhaustion, a control MVC is recorded at the end.
By assessing different contraction types, the difference between genders is analyzed in several dimensions and the results of each contraction type will be used to compare the two groups, males and females.
From all data collected in this study, the linear measures like standard deviation and coefficient of variance will be derived as well as nonlinear methods will be applied to monitor the development of the variability.

Chapter 2

Physiology

2.1 Skeletal muscles

The muscles responsible for locomotion and posture are skeletal muscles. These muscles are also called voluntary muscles as they can contract voluntary compared to cardiac muscles and smooth muscles which are only controlled by the autonomous nervous system. The skeletal muscles are controlled by both the somatic and the autonomous nervous system. [Martini, 2004; Kroemer et al., 1986]

2.2 Motor units

The only activity a muscle can perform is a contraction. Elongation of the muscle is brought from external forces, which lengthen the muscle. A skeletal muscle contraction is performed by the muscle fibers inverted by a motor neuron whose cell body is in the central nervous system. The motor neurons have branching axons which end up in a neuromuscular junction of the motor end-plate at the muscle fibers. A motor neuron can innervate hundreds of muscle fibers, dependent on the refinement of control of the muscle. When a motor neuron fires and innervates the muscle fibers at the motor end-plate the action potentials from the neuron is transmitted to the muscle fibers via a synapse. The synapse lets sodium ions (Na+) diffuse into the muscle fiber. The sodium ions reduce the membrane potential and raise the fibers resting potential (-95 mV) creating an end-plate potential. If the end-plate potential reaches a threshold (-50 mV) an action potential is created in the muscle fiber and sweeps along the muscle fiber in both directions compared to the end-plate.[Beardwell, 1967] When the fibers are activated the filaments in the muscle fiber and creates tension for the fiber. The summation of tension in a pool of activated fibers in a muscle creates a contraction. The muscle fibers are innervated by the motor neuron in the middle of the muscle and the interaction of a motor neuron from the central nervous system and muscle fibers is defined as the motor unit. [Martini, 2004; Kroemer et al., 1986]
To maintain a contraction or increase it, the activation of the muscle fibers is sustained by firings from the motor neuron.

2.2.1 Firing rate

The firing rate of the motor unit depends on the required contraction level performed. For a single stimulation firing, a single contraction, or twitch, occurs. One twitch lasts 7-100 msec depending on the muscle. One muscle twitch is not used in any normal activity. A normal contraction is extended by repeated stimulations and when a muscle fiber is stimulated repeatedly, it produces

more tension than a single twitch [Martini, 2004].
A twitch contraction has 3 phases. The latent period, the contraction phase and the relaxation phase. In the latent period the action potential sweeps along the muscle fiber, but the fiber does not produce any tension because the contraction cycle has not started yet. The latent period lasts for about 2 msecs. In the contraction phase tension in the muscle fiber rises and cross-bridge interaction in the filaments occurs. The contraction phase ends about 15 msecs after stimulation. After the contraction phase, the relaxation phase continues for another 25 msecs. In the relaxation phase the number of active cross-bridges declines and thereby the tension of the muscle fiber decreases to the resting level. To perform a sustained contraction at a certain contraction level, the firing rate of the stimulation has to be increased until the relaxation phase is eliminated.[Martini, 2004] A firing rate at 30-40 Hz will result in a sustained contraction [Kroemer et al., 1986]. Examples of different firing rates is shown in figure 2.1.

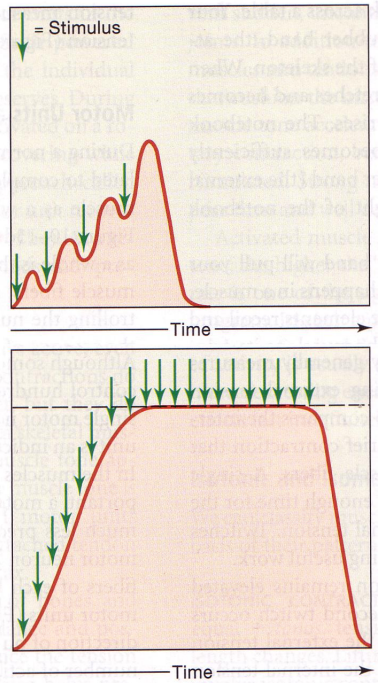

Figure 2.1: *An example of different firing rates. The top drawing shows a firing rate too slow to keep a sustained firing. In the bottom drawing the firing rate is increased and the sustained contraction is performed.*

2.2.2 Recruitment

Dependent on the arm movement, specific motor units are activated by the central nervous system. A contraction of the skeletal muscles begins with recruitment of the smallest fibers. The smallest fibers contract slowly and over time larger and faster contracting muscle fibers are activated [Martini, 2004; Simonsen and Dyhre-Poulsen, 2007]. During a sustained contraction, the recruitment of motor units is done on a rotation basis, which lets units recover to a point of derecruitment. The rotation of motor unit recruitment is called asynchronous motor unit summation.

2.2.3 Contraction type

Basically, the skeletal muscles can perform two types of contractions, isotonic and isometric contraction. In an isotonic contraction the length of the muscle changes and a dynamical movement happens. To perform an isotonic contraction, a resistance threshold has to be exceeded. The resistance can be lifting a weight or simply just move the arm. The speed of an isotonic contraction depends on the tension produced by the muscle and the resistance threshold. For an isometric contraction, the length of the muscle does not change as the tension produced by the muscle never exceeds the resistance threshold. The isometric contraction can be exemplified to lifting a heavy weight. The isometric contraction is used by the body to e.g. reflexively keep the body upright when standing and sitting. [Martini, 2004]

2.2.4 Fatigue

For the skeletal muscle performed a sustained contraction, fatigue is defined as when the muscle no longer is able to perform the required activity of contraction and metabolic processes to continue the supply of needed energy and to remove metabolic byproducts, like lactic acids. [Martini, 2004; Kroemer et al., 1986] Fatigue and the time period to achieve it depend on the contraction of the muscle. A maximal contraction only is maintained for 10 sec before fatigue in the muscle forces one to relax. The lower contraction level, the longer endurance is possible.

2.3 Muscle performance

Two terms are important when considering muscle performance. The first is power which is the maximal tension or force the muscle can produce and the second is endurance which is reflected by the time an individual can perform a certain activity. These two terms are and their performance capability is determined by physical condition and muscle fiber composition.

2.3.1 Types of fibers

In the skeletal muscle, three types of fibers are present. Type I fibers are the smallest muscle fibers and they are also the slowest contracting fibers. These fibers are specialized in performing prolonged contraction. The reason for this prolonged endurance for type I fibers is an extended capillary network at these muscle fibers. Thus, type I fibers have larger oxygen supply compared with other muscle fiber types.
The two remaining types of fibers are called type IIa and type IIb. Type IIa muscle fibers are the fastest fibers in the muscle and they are also the biggest. Type IIa fibers are up to three times as large in diameter as type I fibers. Fast fibers are the most powerful fibers in the muscle, but they fatigue more rapidly compared with Type I fibers because the energy in the fibers are use fast and prolonged activity of the fibers will have to be by anaerobic metabolism. Muscle fibers type IIb is intermediate fibers between type I and type IIa. They resemble type IIa fibers in their characteristics as they are as fast at type IIa fibers, but they more resistant to fatigue. The percentage of different muscle fibers in the muscles is genetically determined and can be significant different between individuals.[Martini, 2004; Simonsen and Dyhre-Poulsen, 2007]

Experimental protocol

Hypothesis

Males can produce greater force than females at the maximal force output. But at low submaximal contractions females have longer endurance time than males. By applying linear and non-linear methods to recordings of forces generated at submaximal levels, the varability in and between the two groups can be examined.

Protocol

Subject information

Subject ID	
Age (dob)	
Weight	
Height	

Subjects

- Two groups, males and females
- 10-12 subjects per group

Force

- 3D force sensor
- 6 channels
- Offset adjust before each recording
  - Fx, Fy, Fz, Mx, My, Mz
- Sampling frequency: 500 Hz
- Gain: 1000
- Low pass filter: 10.5 Hz

- Reference contraction: Maximal Voluntary Contraction (MVC). During MVC the subject is encouraged to perform optimal

Position

- Standing
- The contractions are all static elbow flexions
- The elbow is flexed 90 degrees from stretched
- The dominant arm is used to perform the contractions

Procedure

1. MVC
2. Short contractions
3. Ramp
4. Contraction to fatigue
5. MVC - control

Labview is used to record the data and as visual feedback to the subject. The experiment consists of 5 trials. The first trial is maximal voluntary contractions (MVC) which is recorded 3 times of 3 seconds. After each contraction, the subject has to rest the arm for at least 1 minute before doing the next contraction. MVC yields the reference force use to calculate the force levels for the remaining trials.
The next trial is short contraction at levels from 10% to 90% MVC with a 10% interval. The short contractions has a duration of 3 seconds and the order of the different levels are randomly chosen.
After the short contractions the next trial is a ramp contraction where the subject has to perform a contraction with increasing level of force. The force increases in a continuously manner from 0% to 50% of MVC during a 30 second period.
One minute of rest afterwards a contraction of 20 % of MVC has to be performed until fatigue occurs. When fatigue is reached and the contraction level cannot be held anymore, the trial ends.
At last another MVC has to be performed to monitor the effect of the fatigue contraction.

The data from the experiment is further processed in Matlab by linear and non-linear methods.

Comments to the trials	
MVC	
Short contractions	
Ramp contractions	
Fatigue contraction	
MVC control	

Chapter 3

Methods and materials

In this chapter the procedure of the study will be described, from how the experiment is carried out to the use of statistical analysis for the results.

In this study gender differences in the force output has been examined. For this examination, 20 volunteers have been performing 3 different contraction types each. The contractions are: short contractions, a ramp contraction and an endurance trial contraction.

3.1 Participants

The subjects are represented with 10 males and 10 females. The subject information can be seen in table 3.1. Criterion for inclusion in the study was that the subject was healthy and did not suffer from any neurological disorder. All procedures in the experiment were conducted in accordance with the Declaration of Helsinki.

Gender	Females	Males
Age (years)	24.7 ± 3.9	25.8 ± 2.5
Weight (kg)	65.8 ± 9.3	80.2 ± 7.0
Height (cm)	170.4 ± 7.7	188.9 ± 7.2
Body mass index (BMI)	22.6 ± 2.4	22.5 ± 1.2

Table 3.1: *In the table the anthropometric data for the participating subjects is presented. All values are shown as mean±SD.*

For the experiment the subject used the dominant arm.

3.2 Procedure

To record the force output at the experiment, a 3D force sensor was used to record the force in three dimensions of the elbow flexion. The subjects were instructed to sit on a chair and take a grip on the force sensor with the arm relaxed and the elbow flexed at 90 degrees (see figure 3.1). The arm was not fixated in any way, but the subjects were told to keep the arm still and this position was held throughout the experiment.
The experiment consisted of 5 contraction trials:

1. Maximal voluntary contraction (MVC)
2. Short contractions

3. Ramp contraction

4. Endurance contraction

5. Control MVC

The first contraction trial was MVC recorded three times of 3 seconds to determine strength of each subject. MVC was used as reference contraction during the following contractions. For the short contractions, ramp contraction and endurance contraction force feedback for the elbow flexion was given to the subjects continuously.
The short contractions were nine contractions of 10% to 90% of MVC with a 10% gap in between. The order of the short contractions was random to prevent a priori knowledge of the following contraction level. Each of the contractions lasted 5 seconds with a break of approximate 30 seconds in between.
Following the short contractions, a ramp contraction of 30 seconds was performed. The ramp contraction was increasing in contraction level with 1.5% MVC each second from 5% to 50%MVC.
The subjects performed an endurance contraction going towards fatigue in the elbow flexors. The contraction was performed at 20% MVC and lasted until fatigue occurred and the subject failed to maintain the contraction level.
30 seconds after the end of the endurance contraction a new MVC was performed to examine the effect of fatigue compared with the initial MVC.

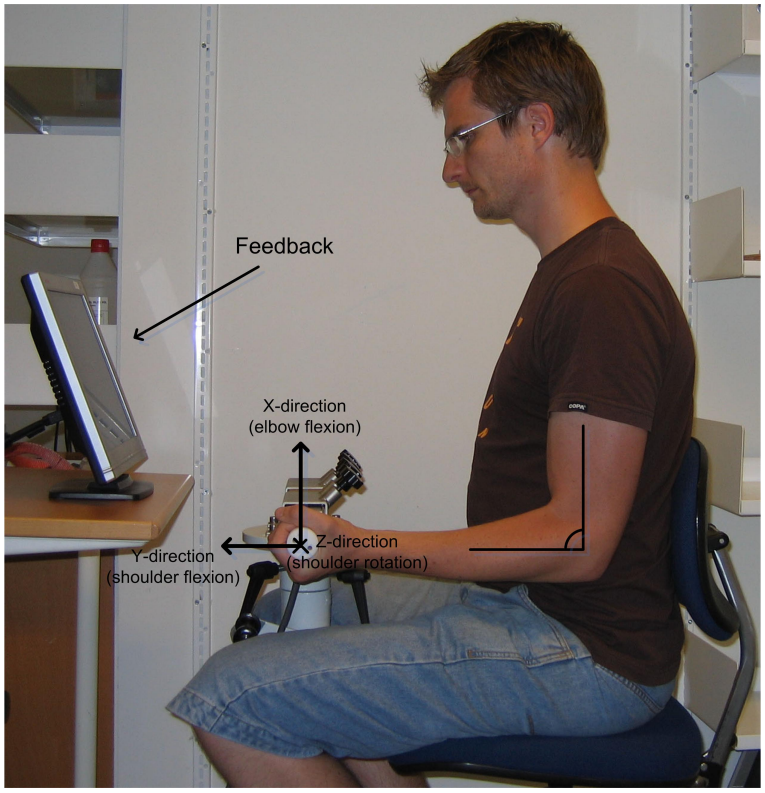

Figure 3.1: *The Experimental setup with the force direction outlined. The monitor is for feedback of the elbow flexion.*

3.3 Data analysis

3.3.1 Acquisition

Forces in the three dimensions of the elbow flexion were measured with 3D force sensors (FS-6, Amti, USA). The output of the force sensor was analogue filtered at 10.5 Hz and a gain of 1000 was used. The signals were AD-converted and recorded through a custom made program in Labview 8.2 (National Instruments), which also operated as force feedback to the subject. All signals were sampled at 500 Hz and saved to further analyze in Matlab R2007a (The MathWorks, Inc).

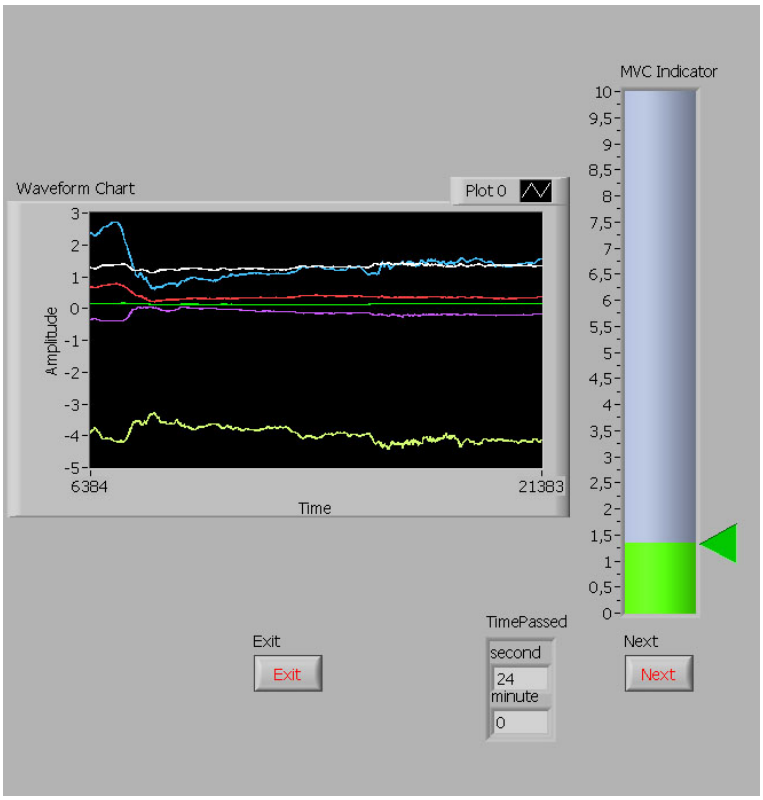

Figure 3.2: *The feedback screen for the experiment. The bar in the right side of the screen will chanbe according to the amount of force applied in the x-direction. The green arrow shows the required force level to reach at the given contraction.*

3.3.2 Calculation of variability

To quantify the amount of variability linear measures like standard deviation (SD) and coefficient of variance(CV) was calculated for the signal. CV was derived from mean and SD of the signal and calculated as $\frac{SD}{mean}$. For the short contractions SD and CV were calculated as one measure for each contraction level, the ramp contraction was calculated in 3 second epochs through the contraction and for the endurance contraction the variability measures were calculated in seven windows of 10 seconds throughout the signal including the start and end of the signal. To examine structure in the variability quantified by the linear methods, a nonlinear method, sample entropy (SaEn)[Richman and Moorman, 2000] was applied the force signal. SaEn was

calculated for the same data bits as the linear measures to gain information of the structure of the variability quantified.

3.4 Statistical analysis

To examine the relationship between genders, contraction level and force direction in the short contractions and the ramp contraction, a 3-way ANOVA was used for all measures of variability amplitude and structure with gender, contraction level and force direction as factors. Statistical analysis for the endurance contraction was also performed with a 3-way ANOVA for all measures of variability amplitude and structure, but with gender, time and force directions as factors. In the analysis of all three contraction types, statistical results were calculated for all main effects as well as all interactions between the factors. The null hypothesis was no difference between the groups, and a 95% significance value was used. For the statistic analysis SPSS 16.0 (SPSS, Inc.) was used. All statistical results are reported by F- and p-values.

Chapter 4

Linear versus nonlinear force signal variability analysis

In this chapter the linear and nonlinear methods applied to the recorded force signals will be described. The methods are standard deviation, coefficient of variance, approximate entropy and sample entropy. The rationale and usefulness of the methods is also assessed.

4.1 Linear methods

To linearly quantify the amount of variability in biomechanic signals, discrete methods extracted from statistics can be used. The most common is the mean of the signal and the standard deviation. The standard deviation is a measure to provide information of how the signal varies. Thus, the standard deviation has been used in general to quantify the variability within and between signals. A way to normalize the standard deviation is by using the coefficient of variance, which is the standard deviation in percentage of the mean.[James, 2004]

4.1.1 Mean and standard deviation

In the literature the traditional methods for quantifying variability originate from statistics which can be applied to both discrete and continuous data. These statistics is usually the sample mean and the belonging standard deviation.[James, 2004]

When calculating the mean of a discrete time series, the calculation is performed with all the samples in the data.

$$x(i),\ i = 1, 2, ..., n, \tag{4.1}$$

where n is the length of the data and x then represent each of the sample in the data.
From all the samples in the time series, the mean of the data is calculated as the sum of the samples divided with the total number of samples as shown in equation 4.2.

$$M = \frac{\sum_{i=1}^{n} x_i}{n}, \tag{4.2}$$

From the mean of the sample, the variance can be calculated as a measure of variability in the time series. It is the total sum of the squared difference between each sample and the mean

divided by the sample size minus one. It is mathematically outlined in equation 4.3.

$$s^2 = \frac{\sum_{i=1}^{n} (x_i - M)}{n-1}, \tag{4.3}$$

s^2 is the variance and n-1 is the degrees of freedom in the time series. The problem by using the variance as a measure of variability, is that the variance is squared. This can make is difficult to interpret physically, for example with a force signal where the mean is in N and the variance will be in N^2. Thus, the standard deviation is used and it is given as the square root of the variance. In the example with a force signal, the standard deviation will be in N like the mean.

$$SD = \sqrt{s^2}, \tag{4.4}$$

where SD is the standard deviation.

4.2 Coefficient of variance

Another method to quantify the variability in the force signal, is to normalize the standard deviation with respect to the mean of the signal, which is the coefficient of variance. The coefficient of variance gives an absolute measure of the variability this is dependent on the magnitude of the force. To normalize the measure of variability, the coefficient of variance can be calculated as the percentage of standard deviation of the mean. The coefficient of variance is calculated as in equation 4.5.

$$CV = \left(\frac{SD}{M}\right) \times 100, \tag{4.5}$$

where CV is the coefficient of variance. [James, 2004]

4.3 Nonlinear dynamics

If a process or compartments of a biological signal has nonlinear structures, a linear measure will fall short of detecting this. For example, the action potentials generated by neurons arise from nonlinear processes. By using nonlinear methods it is possible to detect any nonlinear pattern in a time series. To use a nonlinear method, a few parameters have to be set. From the time series a state space has to be constructed. The state space is a reconstruction of the geometry of the chaotic system which leads to the nonlinear processes in the time series. [Kaplan and Glass, 1995; Abarbanel and Parlitz, 2006] To create the state space, an embedding dimension m and a time delay τ is used.

4.3.1 State space

The state space is constructed from the recorded time series as shown in equation 4.6.

$$\mathbf{u}(i) = \{x(i), x(i+\tau), x(i+2\tau), ..., x(i+(m-1)\tau)\}, \tag{4.6}$$

where $\mathbf{u}$ is the vectors of the state space and x is the recorded time series. τ is the time delay and m is the embedding dimension. The measured time series has only one dynamical variable, but the state space several. It is all dependent on the embedding dimension.

4.3.2 Embedding dimension

For the implementation of nonlinear methods, an embedding dimension is used to reconstruct the geometry of the continuous-time chaotic system from a time series, which is the state space. The embedding dimension m decides the size of the vectors in the state space. [Kaplan and Glass, 1995]

4.4 Approximate Entropy and sample entropy

The linear measures like standard deviation and coefficient of variance quantifies the variability present in the time series. The entropy measures on the other hand have the nonlinear approach and can be used to visualize the structure of the variability. Pincus [1991] The structure of variability in the time series reveal the regularity of the signal and the more regular a time series is, the higher order of structure of variability and vice versa. The approximate entropy and thereby the structure of variability is calculated as the event to event relationship. The entropy measures are able to distinguish between signals that appear similar in the information gained from the linear measures like mean and standard deviation. The value of the entropy will result in a low value for a regular signal while the higher value is reached when the regularity is lower and the structure of variability is in a lower order.

To calculate the approximate entropy(ApEn) and the sample entropy(SaEn), the distance between each vector in the state space has to be calculated. The distance in this study is defined as the maximum absolute difference the vectors. The definition of distance used for the ApEn and SaEn is reported in several studies. [Richman and Moorman, 2000; Pincus, 1991; Kuusela et al., 2002; Khandoker et al., 2008]

$$d(\mathbf{u}(i), \mathbf{u}(j)) = max(|\mathbf{u}(i,k) - \mathbf{u}(j,k)| : 0 \leq k \leq m-1) \tag{4.7}$$

Each of the vectors in the state space will then be used as a template to calculate the difference between each pair of vectors.

4.4.1 Approximate entropy

ApEn is the logarithmic probability that a series of data points a certain distance apart will exhibit similar relative characteristics in the state space [Pincus, 1991].

For the calculation of the approximate entropy, C_i^m must be defined. For this statistics, C_i^m is the total number of the distances from the distance vector (defined above) within the tolerance value, r. It is divided by the total number of distance vector:

$$C_i^m(r) = (N-m+1)^{-1} \sum_{j=1}^{N-m+1} H(r - |d(\mathbf{u}(i), \mathbf{u}(j))|) \tag{4.8}$$

$C_i^m(r)$ is the probability that any vector $\mathbf{u}$(j) is within r of $\mathbf{u}$(i). In equation 4.8 $H(\cdot)$ is the Heaviside step function where the step is 1 if the statement inside is above 0 and otherwise the output is 0. The step function is written in equation 4.9.

$$H(x) = \begin{cases} 1, & if\ x > 0 \\ 0, & otherwise \end{cases} \tag{4.9}$$

The average of the natural logarithm of C_i^m gives Φ^m. Φ^m is the real logarithmic probability of two m-size time series are within a certain distance.

$$\Phi^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log C_i^m(r) \tag{4.10}$$

The approximate entropy is then calculated as the difference between the logarithmic probability of vectors of m data point within the tolerance value, and the same for vectors of size $m + 1$. This gives equation 4.11. [Pincus, 1991]

$$ApEn(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \tag{4.11}$$

Advantages/drawbacks

Approximate entropy is biased. The template approach of the method makes the calculation dependent on sample size. The lower the sample size, the bigger influence of bias. [Richman and Moorman, 2000] When calculating the approximate entropy, the natural logarithm of the number of vectors in the state space within the tolerance is calculated. But to make sure that log(0) is not calculated (this will result in $-\inf$), self matching is allowed, which results in at least one distance between vectors of each template in the state space is within the tolerance r. But this assumption makes approximate entropy biased because the expected value of ApEn(m, r, N) is less than the parameter ApEn(m, r) [Pincus and Goldberger, 1994]. But the bias in approximate entropy is necessary because C_i^m has to be above 0.

4.4.2 Sample entropy

To correct the bias in the approximate entropy, Richman and Moorman [2000] modified the approximate entropy to sample entropy where the self matching is taken into account. When calculating the distances between the vector in the state space $\mathbf{u}$(i) and $\mathbf{u}$(j), $j \neq i$. The variable C_i is defined as the number of the vector $\mathbf{u}$(j) within $\mathbf{u}$(i) then C_i^m is:

$$C_i^m = (N - m - 1)^{-1} \times C_i \tag{4.12}$$

And $\Phi^m(r)$ is now calculated as:

$$\Phi^m(r) = (N - m)^{-1} \sum_{i=1}^{N-m} C_i^m(r) \tag{4.13}$$

The calculation of Φ is done for both m and m+1. $\Phi^m(r)$ is now the probability that two vectors in the state space will match for m points and $\Phi^{m+1}(r)$ is the probability that two vectors in the state space will match for m+1 points.
The sample entropy is calculated as the negative natural logarithm of the probability that two vectors of m points remain within the tolerance for m+1 points, i.e. $\Phi^{m+1}(r)/\Phi^m(r)$. [Richman and Moorman, 2000]

$$SaEn(m, r, N) = -\log\left(\frac{\Phi^{m+1}(r)}{\Phi^m(r)}\right) \tag{4.14}$$

When the sample size N is small the bias of approximate entropy will have a larger influence on the result, but for a large sample size, the approximate entropy and the sample entropy yield similar results. [Kuusela et al., 2002]

Advantages/drawbacks

Sample entropy is a method developed from approximate entropy, and the difference between the two methods is that sample entropy is corrected for the bias approximate entropy makes. The sample entropy is not calculated template-wise as approximate entropy and is not dependent on the sample size. Additionally, a study has shown that sample entropy is more sensible to complex changes in the time series [Lake et al., 2002]. Another recent study has shown that sample entropy is dependent on the rate of frequency in the time series [Aboy et al., 2007], and this could be useful in the understanding of variability in the force time series signals.

Chapter 5

Data acquisition and signal processing

In this chapter the data acquisition and subject-feedback in Labview will be described as well as the signal processing of the data in MATLAB and the implementation of linear and nonlinear methods.

5.1 Data acquisition

For the experiment in this project, a 3D force sensor was used to record the force generated by the elbow flexion. The sensor was supplied by ±10 V and the output of the force sensor was amplified by 1000. The output of the amplifier was six channels of force in three dimensions and torque in the three dimensions. The six channels were AD converted in a 12 bit AD converter (National Instruments) and the signals were recorded in a custom made application in Labview. Labview was used to record the data and to give feedback to the subjects. The feedback to the subjects was the force applied to the force sensor in the upward direction which is the main force direction for the elbow flexion. The Labview feedback screen for the subjects is shown in figure After each contraction in the experiment data from the 6 channels were save in a mat-file named after the subject performing the experiment at the time. The use of a mat-file to store the data was due to the signal processing for the further analysis of the force signal was being done in MATLAB.

5.2 Signal processing

The recorded acquired signal saved in the mat-file is represented in volts, so the first thing to do is to convert the volt signal into forces. Forces in the three dimensions are calculated by the equation:

$$F = \frac{output\ voltage}{gain \times S \times v_0} \tag{5.1}$$

With S being the specific sensitivity of the force sensor in the given direction and v_0 is the supply voltage of the force sensor. The output voltage of the force sensor can range within the supply voltage. Forces for the three dimensions are calculated in the same manner, but with different sensitivities for each force direction.
After this conversion to forces, the force variability measures can be calculated. Depending on the contraction type, the linear and nonlinear measures are calculated of different sample sizes and a different number of calculations.

- In the short contractions one measure is calculated for each contraction level.

- The ramp contraction is divided into 10 windows of three seconds, with each window representing a step of 5% MVC increasing from 5% to 50% MVC.

- For the endurance contraction the length of the recording depends on the fatiguing of the subject, so the force variability measures are calculated for seven windows throughout the contraction. Each window is 10 seconds of duration and is present at %, 16.7%, 33.3%, 50%, 66.7%, 83.3% and 100% of the endurance time. The use of time windows is visualized in figure 5.1.

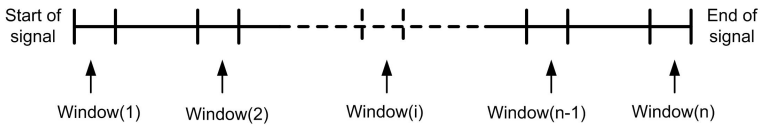

Figure 5.1: *The figure shows how the variability measures are calculated for the signals in the contraction*

5.3 Implementation of the methods

The short contractions are as mentioned above calculated with one measure for each contraction level. Thus, the methods of standard deviation, coefficient of variance, approximate entropy and sample entropy are calculated ones of each dimension in the contraction level.
In the calculation of the variability measures for the ramp contraction and the endurance contraction, a sort of continuous approach to the use of the methods on the discrete signal is taken due to the windowing. As an example, the implementation of the discrete methods is shown in equation 5.2 for the standard deviation.

$$SD_i = \left(\frac{\sum_{j=1}^{n} (x_{ij} - M_i)^2}{n-1} \right)^{\frac{1}{2}}, \tag{5.2}$$

where the only difference is the indexing of the output. The coefficient of variance which is calculated from the standard deviation and the mean is calculated in the same manner.

$$CV_i = \left(\frac{SD_i}{M_i} \right) \times 100 \tag{5.3}$$

5.3.1 Nonlinear methods

To create the state space used in the calculation of the approximate entropy and the sample entropy, embedding dimension m and time delay τ has to be set. According to the literature m = 2 and $\tau = 1$. The tolerance level used in calculating the probabilities for approximate entropy and sample entropy is set to 20% of the standard deviation [Slifkin and Newell, 1999; Kuusela et al., 2002].

5.3.2 MATLAB

The implementation in MATLAB consists of six m-files to calculate the variability measures SD, CV, ApEn and SaEn. For each contraction type, the measures are calculated, so the implementation is divided into three parts. The m-files used are:

- `main_shortC.m`
- `main_ramp.m`
- `main_endurance.m`

Each file provides the number of calculations described above for the contraction types. In each of the main-files, two functions is called; `LinearMethods()` and `NonLinearMethods()`.

LinearMethods()

In the function `LinearMethods()` the linear measures are calculated. For Epoch of 1 second and an overlap of 10% the force mean, standard deviation and coefficient of variance is calculated. Depending on the number of windows to be calculated and the length of them, the calculated values are averaged and used as output.

- **Input:** Force signal, sampling frequency, number of windows and the size of each window.
- **Output:** 3 arrays with the length of the number of windows. Mean force value, standard deviation and coefficient of variation.

5.3.3 NonLinearMethods()

In the function`NonLinearMethods()` the nonlinear measures approximate entropy and sample entropy are calculated. Initially the time windows to calculate the approximate and sample entropy are decided from the length of the time window and the sampling frequency. Then the arranged force data is used as input to the function `AproxEntropy()`.

- **Input:** Force signal, number of time windows and the length of the time windows
- **Output:** Calculated arrays for approximate entropy and sample entropy. The length of the arrays is equal to the number of time windows

5.3.4 AproxEntropy()

In the function `AproxEntropy`, approximate entropy and sample entropy is implemented. The procedure is like described in worksheet 4. The state space is derived initially by the use of embedding dimension m:

```
for i = 1:D-1,
    for j = 1:m+1,
        x(i,j) = data(i+j-1);
    end
    for j=1:m,
        y(i,j) = data(i+j-1);
    end
end
```

where `data` is the force data. `y` is the state space for m and `x` is the state space for m+1. Then matches within 20% standard deviation of the force signal are found for every template:

```
for j = 1:D-1,
    ww(j) = max(abs(y(k,:)-y(j,:)));
    w(j) = max(abs(x(k,:)-x(j,:)));
end

no_u_r1 = find(w <= radius);
no_u_r2 = find(ww <= radius);
```

`ww` is the maximum absolute difference for the state space of m, and `w` is the maximum absolute difference for the state space of m+1. `radius` is the 20% tolerance level and all matches are counted in the variables `no_u_r1` and `no_u_r2`. From the number of matches, the approximate entropy and sample entropy can be calculated as described in Richman and Moorman [2000].

- **Input:** Force data
- **Output:** One measure of approximate entropy and sample entropy

5.3.5 Source code

For further look in the MATLAB programming, all source code is on the attached CD-ROM together with force data.

Chapter 6

Results

In this chapter the results from the analysis of the recorded force data will be presented.

6.1 MVC

As the initial part of the experiment, MVC was recorded. MVC was used as a reference contraction throughout the rest of the experiment. At the end of the experiment after the endurance contraction, a new MVC was recorded to see the effects of fatigue. In table 6.1 MVC for males and female are listed.

MVC (N)	Before	After
Females	152.5±18.4	116.9±19.1
Males	272.9±61.9	219.0±49.5

Table 6.1: *The mean MVC for females and males with the standard deviation. A 2-way ANOVA reveals difference between genders ($F=70.9$, $p<0.01$), difference between MVC before and after the experiment ($F=11.5$, $p<0.01$), but no significant difference in the interaction of the two parameters ($F=0.5$, $p=0.49$).*

The absolute force level was higher for males than for females. The maximum force was lower after endurance contraction.

6.2 Short contractions

From MVC the contraction levels for the short contractions were set. Statistical results for standard deviation (SD), coefficient of variance (CV), approximate entropy (ApEn) and sample entropy (SaEn) are shown in table 6.2 on the following page. The significant results are:

Gender: SD, ApEn and SaEn were larger for males compared with females. CV was higher for females than males.

Contraction level: SD increased with contraction level. ApEn and SaEn increased up to approximate 40% MVC and then decreased.

Force direction: SD was larger for x-direction compared with y- and z-direction and y-direction was larger than z-direction. CV and ApEn were larger for z-direction compared with x- and y-direction and the y-direction was larger than the x-direction. SaEn was larger y- and z-direction compared with the x-direction.

For the interaction between gender and contraction level: SD was larger for males compared with females in the highest contraction level, but no difference was found for the lowest contraction levels.

The interaction between gender and force direction: SD was larger for males compared with females in x-direction compared with y- and z-direction and SD was larger for males compared with females in the y-direction compared with the z-direction. CV was larger for females compared with males in y-direction compared with x- and z-direction.

The interaction of contraction level and force direction: SD increased more in contraction level for x-direction compared with the y- and z-direction, SD in the y-direction increased more in contraction level than in the z-direction. ApEn and SaEn for x-direction increased up to approximate 40% MVC and then decreased. For y-direction ApEn and SaEn generally increased from the lowest to highest contraction level and for the z-direction, ApEn and SaEn decreased with contraction level.

The interaction of all three factors, gender, contraction level and force direction: SD was larger for males in the highest contraction levels in the x-direction compared to females, lower contraction levels and y- and z-direction.

In figure 6.1 on the next page the results of the contractions are presented.

	SD		**CV**		**ApEn**		**SaEn**	
	F	p	F	p	F	p	F	p
Gender (G)	92.97	**<0.01***	12.11	**<0.01***	4.80	**0.03***	5.24	**0.02***
Contraction level (CL)	48.71	**<0.01***	0.62	0.77	4.59	**<0.01***	4.15	**<0.01***
Force direction (FD)	54.50	**<0.01***	100.55	**<0.01***	27.09	**<0.01***	25.92	**<0.01***
G×CL	10.84	**<0.01***	1.00	0.44	0.86	0.55	0.77	0.63
G×FD	6.31	**<0.01***	7.47	**<0.01***	0.93	0.40	0.98	0.38
CL×FD	4.01	**<0.01***	0.74	0.75	2.05	**0.01***	1.92	**0.02***
G×CL×FD	1.64	**0.05***	0.92	0.54	0.61	0.88	0.57	0.91

Table 6.2: *The results of a 3-way ANOVA for the short contractions. The statistic was performed for the variability measures standard deviation (SD), coefficient of variance (CV), approximate entropy (ApEn) and sample entropy (SaEn). The factors were gender (males and females), Contraction level (10, 20, 30, ..., 90 %MVC) and force direction (x, y and z). Significant differences are marked by an asterisk(*).*

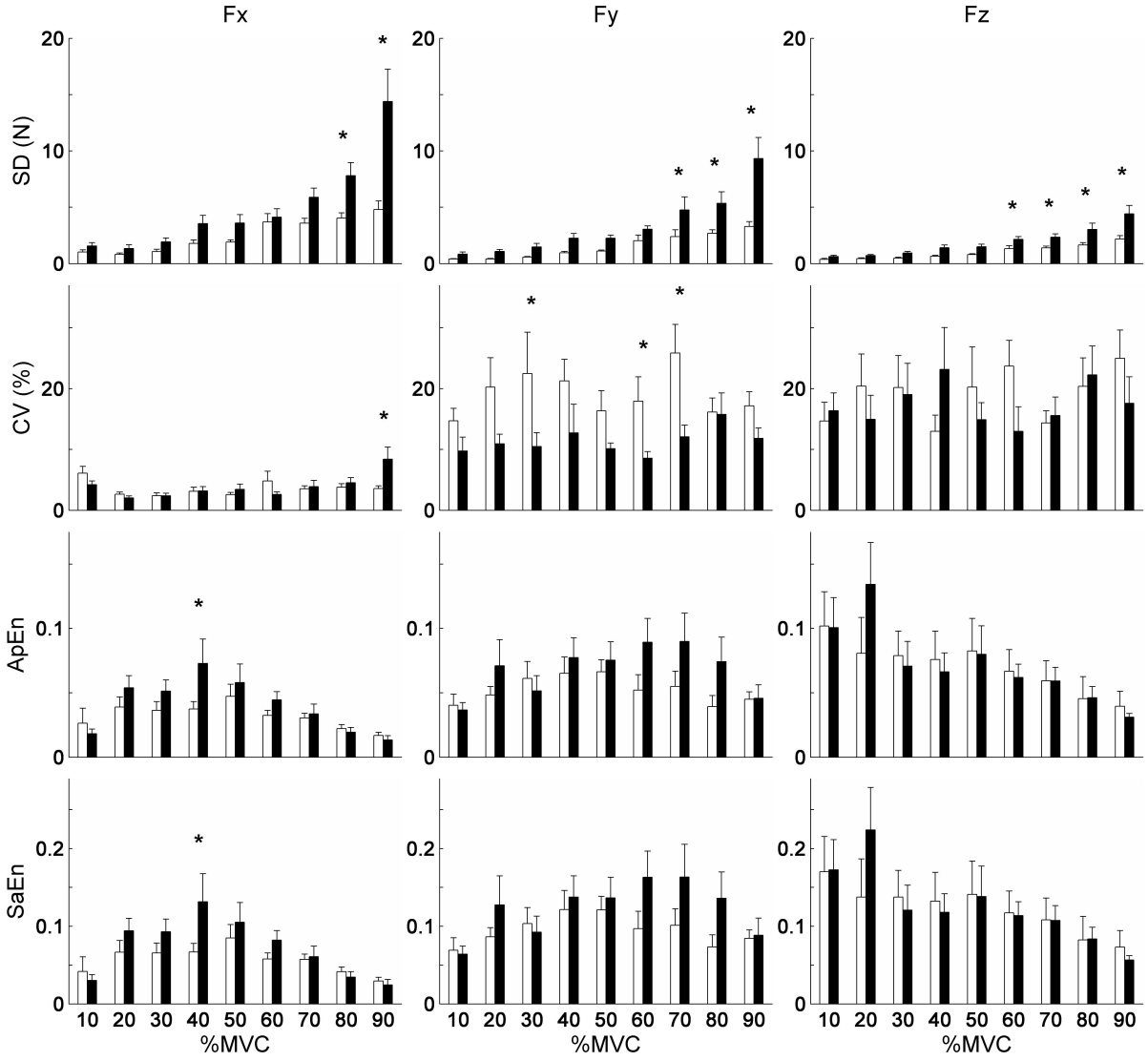

Figure 6.1: *Mean + SE of SD, CV, ApEn and SaEn for force in x (elbow flexion), y (shoulder flexion) and z-direction (rotation) as a function of contraction level. White bars are females and black are males. Asterisk (*) marks significant difference between genders at the respective contraction level.*

6.3 Ramp contraction

The results of the ramp contraction are shown in figure 6.2 on the facing page. The statistic results of the ramp contraction are given in table 6.3. The significant results are:

Gender: SD, ApEn and SaEn were larger for males compared with females. For CV females were larger than males.

Contraction level: SD, ApEn and SaEn were larger for high contraction levels compared with low.

Force direction: SD was larger for the x-direction compared with y- and z-direction. CV, ApEn and SaEn were lower for x-direction compared with the y- and z-direction. No difference was found in between the y- and z-direction in any measure.

The interaction between gender and contraction level: SD, ApEn and SaEn were larger for males at higher contraction levels compared with females.

The interaction between Gender and force direction: CV was larger for females in the y-direction compared with males. No difference was found for x- and z-direction.

The interaction between contraction level and force direction: ApEn and SaEn were larger for higher contraction levels compared with lower in the x- and y-direction. No difference was found in the z-direction.

The interaction of all three factors, gender, contraction level and force direction: No difference was found.

	SD		**CV**		**ApEn**		**SaEn**	
	F	p	F	p	F	p	F	p
Gender (G)	217.42	**<0.01***	26.24	**<0.01***	12.44	**<0.01***	12.62	**<0.01***
Contraction level (CL)	15.85	**<0.01***	3.39	**<0.01***	29.76	**<0.01***	31.18	**<0.01***
Force direction (FD)	61.20	**<0.01***	61.09	**<0.01***	142.40	**<0.01***	136.70	**<0.01***
G×CL	2.52	**0.01***	0.78	0.64	5.32	**<0.01***	5.54	**<0.01***
G×FD	1.60	0.20	6.46	**<0.01***	0.75	0.48	0.76	0.47
CL× FD	0.16	1.00	0.31	0.99	2.01	**0.01***	1.99	**0.01***
G×CL×FD	0.18	1.00	0.15	1.00	0.58	0.91	0.62	0.89

Table 6.3: *The results of a 3-way ANOVA for the ramp contraction. The statistic was performed for the variability measures standard deviation (SD), coefficient of variance (CV), approximate entropy (ApEn) and sample entropy (SaEn). The factors were gender (males and females), Contraction level (5, 10, 15, ..., 50 %MVC) and force direction (x, y and z). Significant differences are marked by an asterisk(*).*

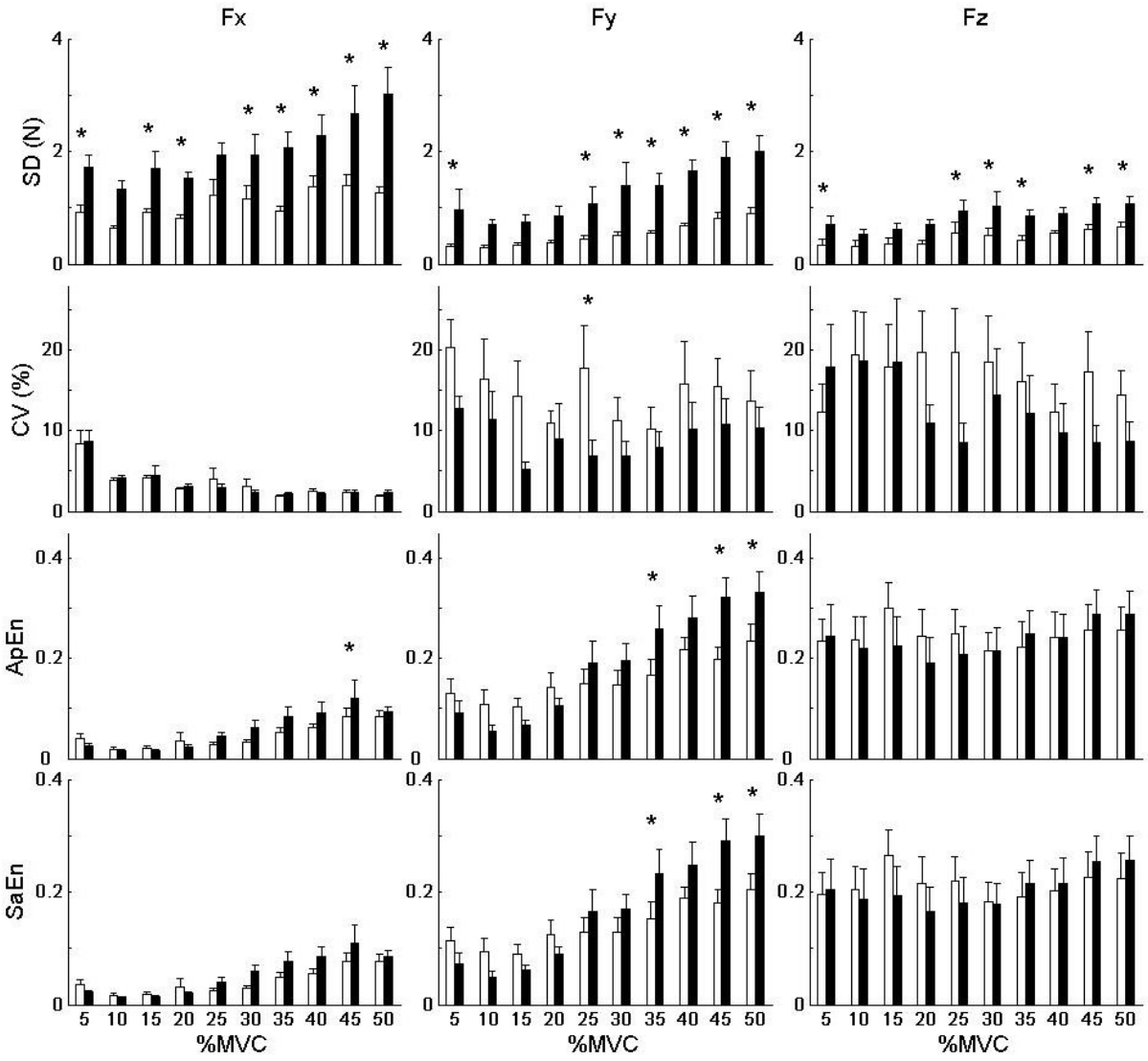

Figure 6.2: *Mean + SE of SD, CV, ApEn and SaEn for force in x (elbow flexion), y (shoulder flexion) and z-direction (shoulder rotation) as a function of contraction level. White bars are females and black are males. Asterisk (*) marks significant difference between genders at the respective contraction level.*

6.4 Endurance contraction

The main trial in the experiment was an endurance contraction at 20 % of MVC. The contraction lasted until the subjects failed to maintain the required force level due to fatigue. The mean length for each gender was 682.8 seconds for females and 344.8 seconds for males. A one-way ANOVA test shows significant difference in the endurance time ($F(1, 18) = 7.5$, $p = 0.01$).
In figure 6.3 on page 40 the result for the endurance contraction is presented. All statistical results are shown in table 6.4 on the next page. The significant results are:

Gender: SD, ApEn and SaEn were larger for males compared with females. CV was larger for females compared with males.

Contraction time: SD and CV increased with contraction time.

Force direction: SD was larger for x- and y-direction compared with the z- direction. CV was larger for y- and z-direction compared with x-direction. ApEn and SaEn were larger for z-direction compared with x- and y-direction.

The interaction between gender and contraction time: SD was lager for males, as SD increased with contraction time compared with females.

The interaction between gender and force direction: SD was larger for males in all force directions compared with females.

The interaction between contraction time and force direction: SD increased with contraction time in the x- and y-direction compared with the z-direction. CV increased in the y- and z-direction with contraction time compared with the x-direction.

The interaction of all three factors, gender, contraction time and force direction: No difference was found.

	SD		**CV**		**ApEn**		**SaEn**	
	F	p	F	p	F	p	F	p
Gender (G)	186.21	**<0.01***	4.54	**0.03***	7.74	**<0.01***	8.18	**<0.01***
Time (T)	34.10	**<0.01***	8.47	**<0.01***	0.91	0.49	1.01	0.42
Force direction (FD)	30.03	**<0.01***	141.13	**<0.01***	19.58	**<0.01***	15.48	**<0.01***
G×T	4.07	**<0.01***	0.18	0.98	0.48	0.82	0.19	0.98
G×FD	3.31	**0.04***	1.28	0.28	0.08	0.92	0.01	0.99
T×FD	2.47	**<0.01***	2.18	**0.01***	0.52	0.91	0.27	0.99
G×T×FD	0.24	0.99	0.16	1.00	0.26	0.99	0.19	0.99

Table 6.4: *The results of a 3-way ANOVA for the endurance contraction. The statistic was performed for the variability measures standard deviation (SD), coefficient of variance (CV), approximate entropy (ApEn) and sample entropy (SaEn). The factors were gender (males and females), contraction time (0, 16.7, 33.3, 50, 66.7, 83.3 and 100 % of endurance) and force direction (x, y and z). Significant differences are marked by an asterisk(*).*

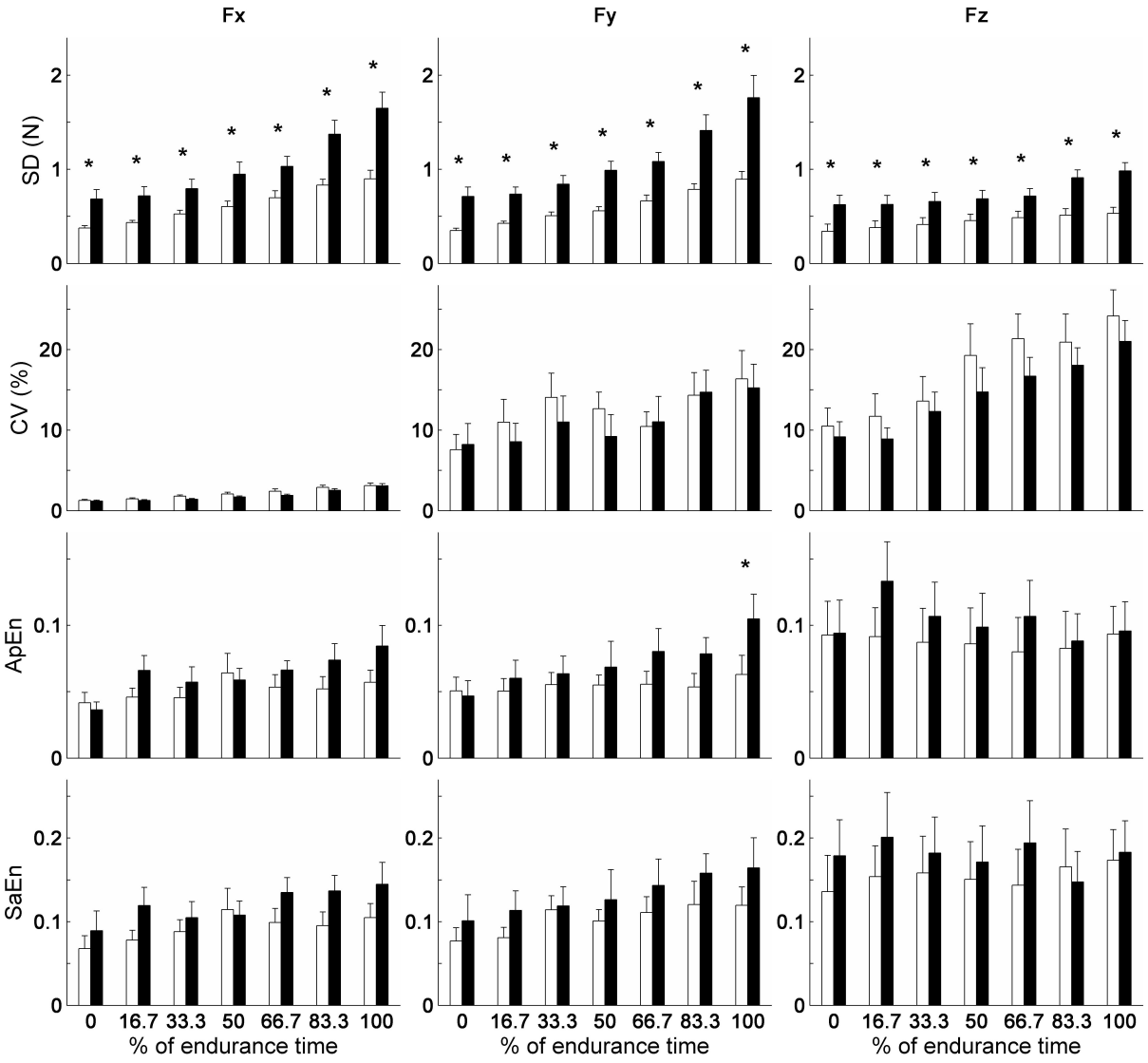

Figure 6.3: *Mean + SE of SD, CV, ApEn and SaEn for force in x (elbow flexion), y (shoulder flexion) and z-direction (rotation) as a function of contraction time. White bars are females and black are males. Asterisk (*) marks significant difference between genders at the respective contraction time.*

Chapter 7

Discussion

The present study aimed at investigating the effects of gender on force variability measured in 3D by means of linear (variability size) and nonlinear (variability structure) analysis during voluntary short duration, ramp and sustained isometric elbow flexions. The findings revealed for the first time that in short, ramp and sustained contractions: (i) the size and the structure of the force during voluntary contraction were not only affected in the direction of force exertion (elbow flexion) but also in the other two directions (shoulder flexion and rotation), (ii) gender played a role in force variability, females being usually characterized by lower amount (SD) and structural complexity (ApEn and SaEn) than males, (iii) the size of variability increased with contraction level up to 100% MVC while the structure of variability changed according to an inverted U-shape function, (iv) the size of variability increased with contraction time.

7.1 Methodological considerations

To quantify the amount of variability present in the force signals, SD and CV were used. CV shows intra-subject variability and changes in variability. But for inter-subjects comparison, the use of SD can be questionable, since comparison of SD from subjects with different absolute force can be difficult to interpret as the variability arises from different amounts of absolute force [Newell and Corcos, 1993]. This is one of the reasons CV as been calculated in this study, as well. CV is SD relative to the force level and the variability is normalized to be fluctuation in the signal as a percentage of mean.

However, nonlinear analysis is required for analyzing motor control strategies in depth [Sosnoff and Newell, 2006]. These methods include e.g. approximate or sample entropy, correlation dimension, fractal dimension, Liv-Zempel entropy [Kuusela et al., 2002]. Approximate entropy and sample entropy were chosen to describe changes in force signal complexity [Pincus, 1991; Richman and Moorman, 2000]. For the calculation of approximate entropy and sample entropy the embedding dimension and tolerance level have to be set. According to previous studies [Richman and Moorman, 2000; Kuusela et al., 2002], m was set to 2 and r was set to 20% of the standard deviation of the force signal to enable a confident estimation of the sample entropy. Likewise, the epoch length of the signal to calculate sample entropy was given. The use of a fixed m can be questioned [Lake et al., 2002] and other studies have suggested using a technique of calculating false nearest neighbors [Hegger and Kantz, 1999; Nichols and Nichols, 2001], since it can give the true value of the embedding dimension and finally the clearest result. If the embedding dimension is not set to fit the deterministic signal, then the result can reflect some sort of random, as the embedding dimension is given as the number of dimensions needed to unfold the structure of the system or signal [Stergiou et al., 2004]. However, the choice of

a fixed embedding dimension and tolerance level is sounded for group comparison purpose of sample entropy values but one should be careful as the sample entropy values obtained depend on embedding dimension, tolerance level, sample frequency, epoch length.

The choice of both calculating approximate entropy and sample entropy was examine the influence of the bias of self-matches on the results. The results of approximate entropy and sample entropy are similar for all measures and all contraction types. The bias which SaEn corrects is minimized with large samples sizes [Richman and Moorman, 2000], and in this study, the smallest sample size used to calculated the variability measures from were 3 seconds, which is 1500 samples. The signal of recorded force output is not very stochastic and the chances of finding matches are good. If a large amount of matches for the templates are found, the self-matches have only little influence and the bias is minimal.

7.2 Effect of force direction on force variability

Studies assessing force variability have generally focused on mono-directional force exertion omitting to consider possible changes in direction during force exertion. The present study considered this aspect as forces were measured in 3D enabling to assess changes in the two other directions. The type of isometric contraction performed consisted of elbow flexion. Moreover, visual feedback was only given in the elbow flexor direction. However, the size and the structure of the force during voluntary contraction changed also in shoulder flexion and rotation directions. The analysis of force in several directions for elbow flexion could give an enhanced insight to the coordination of muscles and recruitment of motor units. But such studies combining 3D force sensors and muscles activity assessment have not previously been conducted for the biceps brachii. The observed changes in the size and structure of variability occurring in 3D even during mono-directional movement can be explained by a lack of control of the subjects' dominant arm position as the actual arm position was solely controlled by the experimenter and/or most likely compensatory mechanisms like co-contraction and changed agonist/antagonist relationship aiming at maintaining the same force output during sustained contraction [Ervilha et al., 2004; Rudroff et al., 2008]. The present results argue for the use 3D force assessment for a full interpretation of changes in force variability during increasing level and sustained contractions.

7.3 Effect of contraction level on force variability

For the short duration contractions with increasing contraction levels and ramp contraction, the observed changes in the size and structure of variability are in line with previous results [Slifkin and Newell, 1999]. SD has been reported to increase exponentially while CV decreased. In the short contractions, CV remained low during elbow flexion, this could be due to failure in reaching the required level of contraction at high sub-maximal contraction levels. In the ramp contraction on the other hand, CV decreased. A hypothesis regarding change in variability with increasing contraction level is that the variability would also increase. In this study, SD increased exponentially (Figure 2) as it has also been reported earlier [Slifkin and Newell, 1999; Tracy et al., 2007], but the variability relative to the force level (i.e. CV) at the different contraction levels did not change while during ramp contraction CV decreased slightly with increasing contraction level. This can be expected as SD increased exponentially with force increasing while the force increase was linear resulting in a decreasing CV as shown earlier [Sosnoff and Newell, 2006]. For the structure of the variability, my result also agrees with the results found by Slifkin and Newell [1999]. Approximate entropy and sample entropy increased up to approximate 40% MVC and then decreased. The inverted U-shape of variability structure in the force signal has previously

been shown [Slifkin and Newell, 1999]. These findings suggest that the recruitment of new motor unit during short duration and ramp contraction does not affect the structure of force variability. Thus, the present study confirm and expand to the whole contraction range that the size and structure of force variability could be governed by separate control processes as proposed by Sosnoff and Newell [2006].

7.4 Effect of endurance time on force variability

The endurance time in the study confirmed difference between genders as reported earlier [Maughan et al., 1986; Hunter and Enoka, 2001; Sato and Ohashi, 1989]. This was bagged by the findings of increased variability also reported earlier [Hunter and Enoka, 2001]. The amount and structure of force variability increased slightly during the endurance contraction but not significant.

7.5 Effect of gender on force variability

7.5.1 contraction level

The development of variability measures in the short duration and ramp contraction was present for both males and females, but SD in the elbow flexion showed significant difference between genders throughout MVC levels, with males showing larger SD than females. For CV, the result was opposite. Gender differences at different contraction levels were expressed by larger amount of variability (SD) for males compared with females and this result could indicate that males have a elevated activity in the biceps brachii muscle compared with females due to higher absolute force level [Hunter and Enoka, 2001] and that muscle activation pattern are different among genders [Ge et al., 2005; Yoon et al., 2007]. The complexity of the force signal was also higher in males compared with females arguing again for gender depend force control strategies.

7.5.2 Endurance time and contraction

For SD a general gender difference occurred throughout the entire contraction, as SD for males were larger compared with females in all force directions. CV showed as expected, the opposite result with females having larger values than males (see methodological considerations). The results concerning gender effects on CV agrees with a recent result from Yoon et al. [2007]. The sample entropy differed also between genders, with males having higher force signal complexity than females similar to the difference observed during increasing force level.
Muscle fatigue is found to alter biomechanical movement patterns [Gates and Dingwell, 2008]. Beside fatigue effects on force variability, the present gender-dependency in the amount and structure of force variability could be due to discrepancies in muscle activation pattern among genders [Ge et al., 2005; Yoon et al., 2007]. During an intermittent fatiguing task, males are reported to require a greater rate of descending drive to maintain the requested force level compared with females [Hunter et al., 2004]. Moreover, an increased accumulation of metabolites in the males' muscle compared with females most likely resulted in an increased afferent feedback to spinal and supraspinal centers [Gandevia, 2001]. This in turn will influence maximum voluntary activation after the endurance task (see Table 2). Fatigue was similar for males and females in line with Yoon et al. [2007] but the males are reported to fatigue more than the females because females experience less peripheral fatigue [Hunter et al., 2006]. All in all, these differences could account for the difference in size and structure of force variability observed in males during an endurance contraction. Contrary to what was observed during short duration or

ramp contractions, the control mechanisms influencing the size and structure of force variability during sustained contraction could be unified to sustain the desired force level.

7.6 Conclusion

The results of this project showed that changes in the size and structure of force variability differed with increasing contraction level and increased similarly with contraction time.This could be due to separate control processes influencing force variability during short and sustained isometric contractions.

The analysis of force variability in 3D showed that the amount and structure of force variability changed in 3D even during mono-directional force exertion, and amount and structure of variability were higher in males compared with females arguing for gender-dependent force control mechanisms.

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