The role of the Neuromuscular Control Mechanism in Motor Output:

Do Individuals Share Muscle Activation Features?

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SUMMARY

Since the electromyographic (EMG) signal is "a global measure" of MU activity and mirrors the physiology of a muscle as well as neuromuscular features [8], abnormalities in both the central control of muscles and the anatomical and physiological properties of the muscle fibres should be reflected in the EMG signal. Although effects on the EMG signal could be pronounced and significant, it's difficult to differentiate within any EMG signal the source of these alternations because many factors influence this signal in various manners [8].

The EMG recorded using surface-based electrodes, is a well-established, non-invasive tool for the assessment of muscle activity [5, 11], neuromuscular activity [2, 8, 14] and neuromuscular control strategies [6, 8, 10, 18, 29, 30]. The combination of EMG and the non-linear time-frequency analysis described by von Tscharner [24] allows the quantification of time, frequency and intensity content together. This wavelet filter-bank has been specified and adapted for the physiological aspects of EMG signals [27, 28].

The primary focus of this thesis was to investigate and quantify the activation patterns of muscles surrounding the knee joint in healthy females during dynamic tasks by extracting frequency features, and temporal and spatial structures from surface EMG signals. The main goal of the studies was to provide a deeper insight into the muscular behaviour and the role of the neuromuscular control mechanism with respect to motor output in general and between individuals to increase the knowledge about the functional state of muscles that stabilise the knee joint. To achieve the above-mentioned goals, the following questions were asked:

Chapter 2: *Are the spectra of EMG recordings of female athletes that were trained either for sprinting or endurance tasks sufficiently different to allow assigning an athlete to one of the groups?*

Consistent differences in the EMG spectra of *M. vastus medialis* and *M. vastus lateralis* between the two groups were expected during isokinetic knee extension because of the differences in muscle features resulting from various training regimes [22]. According to the classical EMG theory, larger muscle fibres diameter should lead to higher conduction velocity [13] and shifts to higher frequencies were experimentally confirmed [9]. Our results showed, on average, a downshift in the frequency spectra of the sprint-trained athletes compared to endurance-trained ones.

For a correct classification, the information contained in the shape of spectra was relevant, whereas the mean frequency contained not enough information for assigning an athlete to one of the groups. The combination of wavelet-based [24] pattern classification – support vector machine and spherical classification – allowed the classification of unknown spectra with a recognition rate higher than 71%.

The present study has clearly shown that the EMG frequency spectra change systematically with training. Consequently, the EMG signal may reflect the training state of a muscle as a component of the state of the individual and allows monitoring training-related changes in muscles. Nevertheless, pattern classification methods tell us that there are highly significant variations between the EMG patterns, but not where these differences were. So classification methods do explicitly not reveal the changes in the neuromuscular control system.

Chapter 3: *Is it possible to detect synchronisation of activation patterns of thigh muscles while walking by using a wavelet-based EMG signal analysis? Do the neuromuscular control mechanisms use a similar timing raster like the timing for the synchronisation of the muscle activity during gait?*

Especially at heel strike, where the human locomotor system is affected by irregular impact forces, controlled muscle activation strategies, "rapid central processing and accurate motor control of strong muscles" are essential for counteracting the destabilising forces and thus for keeping the joint "mobile but stable" [12].

The EMG powers extracted by the time-frequency analysis [24] (92-395 Hz), over a time period encompassing 200 ms before and 200 ms after heel strike, were sensitive to detect a synchronisation of intensity waveforms between thigh muscles. The observed EMG intensities have reflected

a specific and precise timing around heel strike of the activation of the major thigh muscles while walking. This timing is important to coordinate the co-contraction of *Mm. quadriceps femoris* and its antagonist *M. semitendinosus* (antagonist-agonist interplay) and to achieve a preparatory knee positioning before initial contact. Furthermore, precisely timed co-contraction is needed to preserve a stable knee joint [4, 15-17].

Moreover, the results within any subject and between the individuals have shown that, although there has been a lot of jitter in the locations of the intensity peaks – the muscle activation was clearly controlled – on average, by an activity paced at about 40 ms; however with variable amplitudes. This rhythm was independent of both subject and muscle. The pacing frequency of different subjects were scattered across a small range, thus the averaging of the individual waveforms has resolved the pacing properties of the neuromuscular control. Our result agrees with earlier findings showing rhythmicity in skeletal muscles [3, 21, 23, 25, 26] and has supported the idea of previous studies that these temporal patterns and rhythms are represented by the central drive to muscles [1, 3, 7, 19-21, 23, 25, 26].

The understanding of the mechanism underlying neural control is complex, whereby typical characteristics as triggering to heel strike and time dependence of the peak activation were present in all muscles across individuals.

Chapter 4: *Are the dominant activation strategies – extracted from the EMG signal recorded while subject are walking at their self-selected speed – equal between individuals?*

The inter-subject comparison of EMG signals of five thigh muscles while walking was focused on the intra-muscular coordination, by applying a principal component analysis approach. The findings showed that any activation pattern was a combination of the group activation pattern used by all individuals, two common strategies – either a pre impact muscle tuning or a post heel strike reaction – showing the subject-specific deviations and an unresolved, more random activation pattern. Thus, individuals have a constrained flexibility in how they balance their pre and post heel strike muscle activation. The functional reason why individuals prefer either a pre or a post heel strike activation isn't clear, but both strategies may stand in relation to the impulsive force occurring around heel strike.

Hence, multiple configurations of muscle activation can result in functionally similar movements whereby certain activity profiles such as triggering to heel strike, time dependence of peak activations and a balancing of pre and post heel strike muscle activity were present in all individuals. Further, a correlation between the muscles on the medial side as well as between the muscles on the lateral side of the knee showed that there is – additionally to the within-muscle and within-muscle group controlling – a mechanism regulating the knee rotation. This may be a fine tuning of the muscle activation which controls subtle changes in the interplay of structures surrounding the knee joint due to destabilising forces in order to gain a stable knee joint.

The combination of any of the techniques used in this thesis together with wavelet-transformed EMG signals lead to a useful characterisation of the muscular behaviour and the neuromuscular control mechanism to motor output. Furthermore, one can say that individuals share muscle activation features and activity behaviours, for example, rhythm, triggering to heel strike, pre or post heel strike activation and the shape of EMG spectra if following the similar training regime.

Consequently, beyond the field of rehabilitation, in sports and life sciences might benefit from the knowledge gained in this thesis with respect to the fact that the processed EMG signal reflects the functional state of a muscle as a component of the state of the individual and allows monitoring training-related changes in muscles.

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PUBLICATIONS ARISING FROM THIS THESIS

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C. Huber, C. Nüesch, B. Göpfert, PhC. Cattin, V. von Tscharner. Muscular fine-timing and inter-muscular coordination during walking. *Proceeding at the 13th Congress of the International Society of Biomechanics (ISB),* Brussels, Belgium, July 3-7 2011.

C. Huber, C. Nüesch, B. Göpfert, PhC. Cattin, V. von Tscharner. Detection of muscle activation patterns during gait using Principal Component Analysis. *Proceeding at the 7th annual conference of the German Society of Biomechanics (DGfB)*, Murnau, Germany, May 19-21 2011.

C. Huber, C. Nüesch, B. Göpfert, V. von Tscharner. Principal Component Analysis of patterns of muscle activation in healthy subjects during gait. *Poster at the 9th BioValley Life Sciences Week*, Basel, Switzerland, September 20-24 2010.

C. Huber, B. Göpfert, V. von Tscharner, D. Wirz, R. Brunner. The effect of endurance and sprint training on EMG signals by wavelets analysis. *Proceeding of the 8th World Congress at Performance Analysis of Sport (WCPAS)*, Magdeburg, Germany, September 3-6 2008.

CHAPTER 1

Introduction

ABBREVIATIONS

AP, action potential; *cf*, centre frequency; *CV*, conduction velocity; *EEG*, electroencephalography; *EMG*, electromyography; *MDF*, median frequency; *MF*, mean frequency; *MU*, motor unit; *MUAP*, motor unit action potential; *MUAPt*, motor unit action potential translates to a shape in time; *PCA*, principal component analysis; *SVM*, support vector machine.

GENERAL ASPECTS

Walking, running and cycling seem easy to coordinate, but each of these activities is the motion output of the interaction between the task, the individual and its neuromuscular system, and the environmental demands. Skeletal muscles are the functional unit of the neuromuscular system, which consists of an interaction of muscles, bony, capsular plus ligamentous structures, and the nerves controlling the movement [44]. Hence, multiple systems and structures have to smoothly cooperate hand in hand. It must be noted that muscles aren't only used for propulsion, but also for shock absorption and for imparting and maintaining "functional joint stability" mainly at impact, when the foot hits the ground [44, 73].

The many degrees of freedom of the skeletal system provide humans great flexibility, but make its controlling extremely complex. Even an alteration or some damages to a muscle or structure, which influence the muscle activity, can lead to a misbalances between particular structures, and therefore harm in the movement pattern. In particular at heel strike, where the human locomotor system is affected by irregular impact forces [73], controlled muscle activation strategies are essential for counteracting the destabilising forces, to keep the knee joint solid and mobile.

The focus of the present thesis is on the interrelationship of muscles surrounding the multiaxial knee joint. The knee is – compared to the hip joint – insufficiently stabilised by bony structures alone, and thus, dependent on additional structures like (cruciate) ligaments, menisci and muscles to achieve stability and protection. The investigation of the activation patterns of these muscles is easily justified because (i) an intact and well-functional joint maintains quality of life and independence, (ii) a painful knee contributes to mobility impairment [58] and (iii) the knee as the largest synovial joint is a common location of complaints in the lower limb. Hence, a loss of any interplay between structures surrounding the knee may endanger the function as well as the health of the system and may require an adjustment of the neuromuscular control system.

Electromyography (EMG) recorded using surface-based electrodes, is a well-established, non-invasive tool for the assessment of not only muscle activity [26, 39], but also of neuromuscular activity [11, 31, 62] and neuromuscular activation strategies [27, 31, 37, 86, 122, 124].

In the last decades, the possible ways to analyse EMG signals have been increased through the development of computational tools, software and mathematical algorithms. The various signal processing techniques have simplified the handling of the vast amount of data and their downstream analysis steps. In consequence, more powerful and complex algorithms can be applied to EMG signals extracting detailed features of the signal that allow a deeper and meaningful insight into muscles plus its control mechanisms.

The present thesis focuses on the time, frequency as well as on the intensity content of EMG signals and their association with muscle properties, muscular behaviour and the role of the neuromuscular control mechanism in the context to motor output. In the following, the techniques of data acquisition and analysis, used in this thesis, are shortly introduced.

ELECTROMYOGRAPHY

The surface EMG is a relatively simple non-invasive technique that is well-established for the investigation and the assessment of activation patterns of superficial muscles during dynamic conditions [5, 27, 37, 47, 110]. It supplies valuable information in addition to having a variety of applications in clinical plus biomechanical research, including the diagnosis of neuromuscular disorders [38] and neuromuscular alternations [41] as well as the controlling of myoelectrical prostheses [16, 67, 83, 91].

EMG Signal Recording

The surface EMG records the electrical activity produced within a muscle by using electrode pairs or arrays placed on the skin above a muscle. As a result, the EMG measures the discharge process within multiple of muscle fibres, caused by movements of sodium and potassium ions around the muscle fibres. There are different kinds of electrodes available: needle, fine-wire and surface electrodes. In this thesis, the muscle activity was measured by using round bipolar Ag/AgCl surface electrodes (Noraxon U.S.A. Inc., Scottsdale, AZ, USA) with a diameter of 10 mm and an inter-electrode distance of 22 mm. To get hold of high quality EMG measurements, the skin was shaved and cleaned with alcohol before recording. Then, the electrodes were positioned parallel to the direction of the muscle fibre between the innervation zone and the muscle-tendon interface, according to the recommendations of SENIAM (Surface EMG for Non-Invasive Assessment of Muscles [39]). Then, all electrodes were connected to single differential amplifiers with a band path of 10-700 Hz (Biovision, Wehrheim, Germany). The reference electrode positioned on the tibial tuberosity was necessary for electrical stability. To avoid movement artefacts, cables and electrodes were kept in place by taping to the skin or by elastic net bandage.

Signal Emergence

Ion pumps and ion exchange processes create a resting potential of about -90 mV at the muscle fibre membrane. Thus the potential inside the muscle cell is negatively charged – compared to the outside. When an action potential (AP) spreads along the motoneuron from the spinal cord to the neuromuscular junction, neurotransmitter molecules are released at the neuromuscular junction. This release modifies the membrane permeability via opening ion channels. The sodium's influx depolarises the fibre membrane, following by the potassium's outflow that subsequently repolarises the fibre membrane. Sufficient stimulation leads to a transient change of the potential inside the muscle fibre from its resting value to about 30 to 40 mV.

Moreover, the combination of the muscle fibre APs of all muscle fibres innervated by a certain motor unit (MU) represents a motor unit action potential (MUAP). The MUAPs travel along activated muscle fibres to a shape in time (MUAPt). The translation from MUAP to MUAPt is the result through the conduction velocity (CV), which varies by different muscle fibres, and thus by different MUs [64]. For that reason, the EMG signal is a recording of a weighted summation of spatial and temporal activity of independently activated MUs at the location of the electrode, and so, it is a mixture of signals generated by all innervated fibres within a certain MU due to poor spatial selectivity at the recording electrode pair [26]. That's why the actual EMG signal is both a compound signal [64] as well as "a global measure of MU" activity [30, 31]. Furthermore, the superposition of multiple MUAPts generates an interference EMG pattern at the location of the fix located electrode pair with a random asynchronous distribution of positive and negative amplitudes [84].

Consequently, because MUs are the smallest functional unit of the neuromuscular control, the features of an EMG signal mirror both "peripheral and central properties of the neuromuscular system" and are so dependent on the muscle and its recruitment pattern [31].

Factors Affecting the EMG Signal

The EMG signal depends on specific properties of the MUAPs, which are influenced by physiological, anatomical plus biochemical characteristics of the innervated muscle fibres [26, 123]; and thus by the CV [64]. Especially muscle properties that change the size of a muscle as well as its composition and its neuromuscular control (i.e. MU recruitment) contribute to variations in the EMG signal [26, 123]. Kupa [56] has shown in an in vitro study about rat muscles that AP of faster MUs have higher CV and would contribute higher frequency characteristics to the EMG signal. Traditional EMG theory says that the ability to infer information on MU recruitment and fibre-type proportions from a spectral analysis of a surface EMG signal is based on the relation between the average CV of an active MU and fibre-type proportion and based on the link between changes of the average CV and the changes in the spectral properties [29]. These assumptions are not fully evaluated and have been discussed in a recent point-counterpoint article [29, 113].

A boost in synchronised MUs caused – among others – by strength training [89, 90] results in a decrease of frequency content in the signal [68, 89, 119] and in a downshift of the mean frequency (MF) [48, 64, 113]. What's more, the subcutaneous tissue between the active MU and the electrode has a low-pass filtering effect, and therefore, has also a damping force on the recorded EMG signal. The effect of these indirect factors is difficult to limit, to control or to keep constant in experiments. Moreover, for instance, gender [18, 72, 111], age [25, 72, 104], habitual activity [4, 9, 10, 28, 72, 96], immobilisation [9, 25], and also medical records [103] vary between subjects and are expressed in variations in the EMG signal.

Two main disadvantages of recording with surface EMG are crosstalk and movement artefacts [31, 120]. Crosstalk appears when the EMG signal is generated by neighbouring muscles. Movement artefacts can be minimised by fixing cables. In this thesis, effects occurring during intensive exercises, including blood flow, the fatigue state of a muscle [12, 26, 64, 79] and muscle temperature [40] were neglected in the study about gait, but may have a small influence on the frequency content in the knee extension task.

EMG Signal Processing

The aim of EMG signal processing is to decompose the oscillating potential into the time, frequency and intensity characteristics. The rectified signal and the root mean squared value are two classical techniques with computational simplicity to quantify the amplitude of an EMG signal. For the analysis of the frequency content, the Fourier transform has often been applied on EMG signals in general; despite it assuming stationary or quasi-stationary signals, which is unlikely during dynamic tasks. Unfortunately with these approaches, either the frequency or the time component is lost.

Time-Frequency Analysis

Recently, the time-frequency analysis based on wavelets has become a powerful alternative to the Fourier transform, when investigating EMG signals during dynamic conditions [51, 53, 55, 105] because a wavelet-based method assumes non-stationary signals and resolves the signals into intensities in time-frequency space. Time-frequency analysis studies EMG signals in a very short time duration [53], so that the change in timing and frequency content can be assessed at the same time.

Von Tscharner [105] has described a time-frequency analysis, which transforms the EMG signal by decomposing the EMG signal into their time, intensity and frequency content by using a filter-bank of non-linearly scaled specified Cauchy wavelets indexed by j (w_j). Each wavelet is characterised by its centre frequency (cf_j), time resolution and bandwidth (Table 1) and acts as a band-pass filter. The time resolution of the wavelets has been specified to resolve physiologically relevant features of the muscle properties [105]. This wavelet transform yields an intensity pattern $p_{j,n}$ where n is the index of the time points and $p_{j,n}$ is proportional to the EMG power within the frequency band. The result $p_{j,n}$ can be visualised as an EMG intensity pattern by showing a contour plot (time-frequency representation as illustrated in Fig. 1B) where the abscissa represents time, the ordinate shows the wavelets with their frequency bands and the grey scale stands for the intensity of the signal. The highest intensity is black shaded and the lower intensities are in different grey shadings. The grey scale between the centre frequencies is obtained by interpolation.

In contrast to traditional linear wavelet analysis where the time resolution increases with increasing frequency, the non-linear wavelet analysis keeps the time resolution within the physiological relevant time frames [105]. Both the number of wavelets and the parameters of the wavelets depend on the sampling rate.

Also, significant work has been done showing that the spectral aspects observed by applying the wavelet transform corresponded to those obtained by the Fourier transform [4, 52]. Besides, the wavelet transform applied on EMG signals compared to traditional methods has – among others – the possibility of de-noising the signal without distinct appreciable degradation [45] and the option of removing parts of the signal.

For instance, low frequencies (cf_j <7 Hz) that mostly result from movement artefacts [20] can be easily omitted from the entire intensity pattern.

TABLE 1: Parameters of the wavelets* at a sampling rate of 2'400 Hz.

Index *j* of wavelet	w_0	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}
Centre frequency [Hz]	7	19	38	62	92	128	170	218	271	331	395	466	542
Time resolution [ms]	81	53	38	30	25	21	18	16	14	13	12	11	10
Bandwidth [Hz]	12	21	30	40	49	59	68	75	84	94	103	113	122

* Parameters were calculated for scale = 0.3, q = 1.45 and r = 1.959 [105].

The intensity pattern $p_{j,n}$ is the basis for further analysis steps, for instance, in terms of the intensity pattern (time-frequency pattern) (Fig. 1B), the total intensity (time versus intensity) (Fig. 1C) and the frequency spectrum (frequency versus intensity) (Fig. 1D).

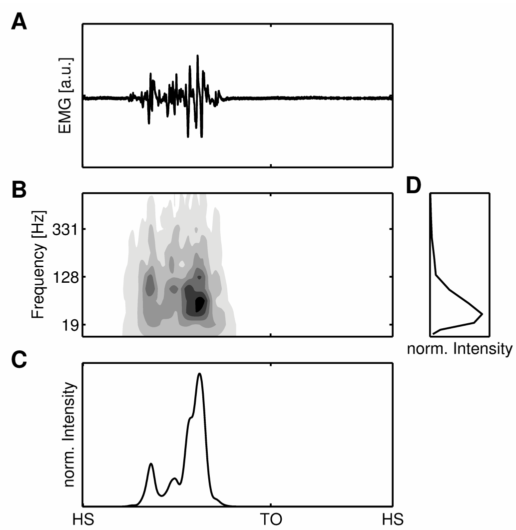

FIGURE 1. Example of a surface EMG signal processing from M. gastrocnemius medialis for one stride, while level walking. Heel strike and toe off occurred at HS and TO, respectively. The graphs illustrate (A) the raw EMG signal, (B) the intensity pattern, (C) the area normalised total intensity and (D) the area normalised frequency spectrum. The grey scale between the centre frequencies in (B) is obtained by interpolation. High intensities are depicted by dark shading, low intensities by white shading.

Application

Von Tscharner and Nigg [113] are convinced that the wavelet-transformed EMG spectra, among other aspects, reflected the task-specific selection of muscle fibres. For instance, while running barefoot, the muscle tuning of the *M. tibialis anterior* before heel strike has resulted in the expression of higher frequencies in the EMG signal than those observed after heel strike [112]. Additionally, it was significantly different at well-defined time points between female and male runners [111]. What was more, Wakeling et al. [117] has reported significant differences in the way individuals responded to prolonged running. The low frequency components decreased in intensity as well as the high frequency information increased in intensity during a 30-min run. Also, von Tscharner [106] has shown that the EMG signal varied between different running trials, but specific features of the signal were present across the subjects. Thus, a wavelet-transformed EMG signal is specific for a task, muscle, gender and subject.

PATTERN RECOGNITION

In many EMG studies, single variables (for example, maximal amplitude, peak value or specific time point) extracted from a data set have been determined by researchers to monitor variations between two groups (for example, subjects, tasks or muscles). By this arbitrary choice of parameters, it is possible that key variables aren't included in the analysis. Besides, most of the time it's a challenge to identify by eye the most relevant features of a signal or a data set for the analysis. During the last years, EMG signals have been classified and identified by the application of diverse pattern recognition approaches. These classification methods allow a statistical check of the differences contained in the patterns, whereby all aspects of the pattern contribute minutely to the final result. In particular, the patterns are classified based either on a priori knowledge or on extracted statistical information.

Hence, it isn't a surprise that recently pattern recognition methods applied on EMG signals covered a wide spread of potential applications, including – among others – automatic speech recognition [15], controlling of upper limb prosthesis [16, 67, 83], automated gait classification [7] or discrimination between early and late rehabilitation [63].

Pattern Classification

Today, both simple and complex pattern classification algorithms are available [8, 22, 23, 34]. They vary in the manner how they define the boundary – the so-called classifier – in a multi-dimensional space that separates the patterns, which are belonging to different classes. The role of a classifier is to adapt and utilise the information it receives from the training data set to separate, the patterns of two classes. In pattern classification, any pattern is compared with one another. To accomplish this, each pattern has to be transformed into a single point in an appropriate multi-dimensional space. Points forming a cluster represent similar patterns, those far away from that cluster, indicating that these patterns are different to the ones forming the cluster. It is anticipated that one can assign each input pattern to a class or to an outlier. A high recognition rate in any classification method applied on EMG patterns can only be reached, if systematic differences in the patterns are reflected between the classes and if the generalisation is efficient in classifying unknown patterns. What's more, this approach supplies information that can be hidden from the eye. Thus, it eliminates the inter-examiner variability.

In this thesis, two different classification methods, the spherical classification [34, 49, 106] and the linear support vector machine (SVM) [8, 22, 23] methods have been applied and their performance has been compared; the latter being mathematically a more demanding method with a rather high computational cost compared to the spherical separation.

Spherical Classification

The spherical classification was described by Fukunaga [34]. One assumes that the points of a class lie in a hollow shell with a shell thickness that is represented by the statistical distribution's border [8, 34]. Any points of representing patterns are positioned in the shell wall and the average of all patterns is somewhere close to the centre of the shell [106]. Hence, a new point in space can be assigned to that class where its distance to the centre of the shell is the smallest. The advantage of a spherical classification is its simplicity.

The spherical classification was recently applied on multi-muscle activation patterns [106, 114] and on EMG frequency spectra [33] to distinguish the EMG pattern of runners according to their shod conditions, of healthy and osteoarthritis patients in accord to their neuromuscular changes and of fencers according to their success in battles.

Support Vector Machine

A general overview of the SVM classifier – a machine learning algorithm – and its mathematical background can be found in Cortes and Vapnik [22]. Among other aspects, an SVM algorithm is a powerful method, because of its high generalisation performance (i.e. error rates of test sets) without the need of a priori knowledge on the variable selection. The SVM algorithm is looking for a classifier, which separates both classes and maximises the distance between the classifier and the closest points [22]. Several studies have shown that the performance of an SVM-based classification was outstanding to other machine learning methods. This includes artificial neural networks, linear discriminant analysis, multi-layer perceptron and radial basis function networks [38, 61, 76].

In the field of gait analysis, the SVM classification has been applied – among others – for the detection of gait modifications in patients with patellofemoral pain syndrome [57], balance impairment [6] or abnormal gait [3]. Regardless of the success of SVM classifiers in a wide scope, there is limited research on the classification ability of an SVM in EMG analysis. In the past, reported SVM studies on EMG signals have focused on controlling and manipulating of prosthesis devices to classify – among others – grasping movements [16, 65, 91]. Recent studies on EMG-based SVM classification have shown that the central and peripheral controlled features in the EMG intensity patterns alter in a systematic manner during a fatiguing run [93] or that various neuromuscular disorders, for example, myopathy and neuropathy, change properties within a muscle [38].

The SVM implementation used in this thesis has been downloaded as freeware from the internet [17] and used in Matlab as a plug-in.

Principal Component Analysis

Pearson [77] was the first person, who has formulated the principal component analysis (PCA) technique in statistics. Mathematically, PCA consists of an orthonormal transformation, which converts the correlated input variables into the new uncorrelated principal components. An overview of the PCA technique can be found in Jolliffe [50]. The PCA is a multivariate statistical technique that can explore data sets by simplifying data structures, reducing data, modelling, detecting of outliers, selecting of variables and predicting classes [121].

Contrary to an SVM classifier, where the data are discriminated into classes, the PCA objectively identifies the general characteristics – the most common features – based on the variations represented in the entire data set.

An EMG-based PCA has been commonly used to analyse data ranging from "macro- to nanolevel", including detection of abnormal gait patterns [71], revealing the existence of real physiological structures about the nature of the coordination of a movement [1] or resolving neuromuscular processes [11]. For instance, PCA has been used to distinguish muscle activity patterns belonging to different shod conditions [110], neuromuscular alternations and disorders [2, 41, 62, 81, 114, 115], gender [59, 111], way of walking [36], level of back pain [60, 78], fatigue [107] as well as hand and finger motions [54, 67]. Moreover in EMG, it is a good tool for de-noising EMG signals from movement artefacts, anatomical variations in the soft-tissue as well as individual physiological variations, because noise has been contained in the highest principal components [82].

This thesis will focus on the classification possibility of PCA by extracting the dominant patterns from the input data set; hence, temporal information is retained.

NEUROMUSCULAR CONTROL

In the last years, there has been much interest in the neural activity of the brain and its role to motion output. Interpreting the content of EMG signals implies the explanation of the brain's intention to contract a muscle.

The extractions of rhythmicity and the muscle synergy from EMG signals are two possible approaches to gain a deeper insight into the muscular behaviour, and therefore, into the neuromuscular control mechanism. While rhythmicity is a more controlling approach, synergism is a holistic functional consideration.

Extraction of Rhythm

Works in the late 1990s have shown a corticomuscular association in the frequency domain – a so-called coherence [85] – between oscillatory activities in the electroencephalography (EEG) or magnetoencephalogram and in the EMG. This synchronisation characterises the linking between the activity in the motor cortex and the muscle activity [13, 14, 21, 69, 74, 87, 88].

In skeletal muscles, rhythmicity in EMG signals at frequencies of 30 to 60 Hz has been noted by Hans Piper [80] during maximal voluntary contractions and this frequency range is termed as Piper band [13]. Rhythms within the Piper bands have been shown to be correlated to central descending drive [13]. Salenius et al. [88] have anticipated that the cortical 40 Hz activity sets the corticomuscular communication's pace.

Recent findings have detected the Piper rhythm directly from the EMG signal without using the coherence analysis with the brain activity [92, 108, 109]. For example, rhythm ranging from approximately 25 to 55 Hz, thus within the Piper band, has been found in *M. abductor pollicis brevis* during isometric contractions [109] and in *M. gastrocnemius medialis* while running [92]. What's more, neuromuscular control mechanisms, extracted in processed EMG signals, have shown a precise pacing with a pacing rhythm, which supposedly reflects the corticomuscular interaction [13, 14, 87, 88, 92, 108, 109].

Furthermore, Stirling et al. [92] have reported in running that rhythm, detected in the wavelet-based intensity pattern, is triggered with respect to heel strike. Moreover, they have supposed that such a temporal coding has reflected aspects of the central control generated within the brain. Additionally, the pacing rhythm varied from subject to subject [92] and decreased in the frequency with fatigue [108]. Von Tscharner et al. [108] have assumed that such a pacing "is a fine tuning of the muscle activation which allows subtle adjustments of the exerted forces".

Extraction of Muscle Synergy

Many investigators have proposed that the central nervous system accomplishes a task of high dimensionality by simplifying multifaceted motor patterns based on combinations of fixed muscle groups [24, 98], encoded as patterns in the spinal cord and brain. Several authors have decomposed EMG patterns of numerous muscles into a few muscle synergy patterns [97, 99] or muscle modules [19]. An approach like this explains an activation pattern of any muscle by linear weighted combinations (identical to the principal component scores) of a number of time varying muscle synergies (identical to the principal component vectors) [42]. Muscle synergy can be identified from EMG patterns, recorded from multiple muscles by using different factorisation algorithms such as factor analysis, independent component analysis, non-negative matrix factorisation or PCA. The basic characteristics of the synergies were independent of the applied algorithm [46, 97].

Previous muscle coordination studies have shown that many movements in humans, for example, hand postures [1, 24, 95, 118], postural tasks [94, 95], cycling [43, 116] or locomotion [19, 35, 47, 70, 75] are neural predetermined [99], and therefore, can be decomposed into a linear combination of just a few muscle synergies. Like, in humans, six or fewer muscle synergies are able to control 16 muscles of the lower back and thigh during postural control [95] as well as to control between 8 and 32 different muscles in locomotion [19, 35, 47, 70]. Also, recent synergy studies have figured out that movement correction involves more synergies than the movement initiation [32], that untrained and experienced rowers have the same three muscle synergies [101] and that fatigue doesn't change the organisation of the muscle coordination [100].

In consequence, the complexity of muscular control could be reduced to a small number of synergy patterns, which are temporarily constrained to act as a single unit to produce a muscle activation pattern. This concept of muscle synergies is a holistic functional consideration detecting certain features that are common in many muscles. Thus, it considers the inter-muscular coordination.

Aim of this Thesis

Since the EMG signal is "a global measure" of the spatial and temporal activity of many MUs, one has to be aware that the EMG characteristics mirror the physiology of a muscle [31]. In recent years, variables related to the frequency content of an EMG signal (for example, MF, median frequency (MDF)) are used to gain physiologically relevant aspects of a muscle (for example, fibre diameter or fibre-type proportion) and its behaviour during various types of dynamic tasks [51, 66, 102]. Electromyography is mainly related to the neural output from the spinal cord and, thus to the number of activated MUs and their discharge rates as well as the fibre membrane properties such as the muscle fibre CV [31]. Thus, changes and abnormalities in the central and peripheral controlled features in the muscle fibres of the underlying muscle should be mirrored in the activation pattern, and thus, in the EMG signal. Although these effects on the EMG signal are pronounced and significant, it is difficult to differentiate the sources of many factors influencing the signal in various manners [31]. Consequently, the EMG signal reflects the functional status of a muscle. It is therefore of interest, if one can use the EMG signal or parameters gathered from the EMG signal to detect systematic modifications caused by changed central and peripheral properties.

In the past, researchers have naturally extracted single variables (e.g. maximal amplitude, MF or MDF) from the EMG signal in advance to monitor variations between subjects, tasks or muscles. This approach considers not the information of the whole EMG signal and it could be possible that relevant information isn't included in the analysis. When applying classification methods on EMG signals, all aspects of a pattern are considered and contribute minutely to the final result. Among others, it has discriminated EMG intensity patterns between healthy and patients suffering from osteoarthritis [114]. Hence, classification methods yield a more global, holistic view of any EMG pattern. Nevertheless, pattern classification can reveal the existence of highly significant variations in the EMG pattern but not where these differences were. So the classification methods don't explicitly reveal which part of the EMG pattern contains the information required for a correct classification.

As a result, the understanding of mechanisms and strategies underlying the control of the neuromuscular system and in the way it innervates muscles are essential. A loss of interplay between any components may imperil the function and health of the human system. There is a growing need for a deeper insight into the flexible nature of human muscle activity by focussing on the inter- and intra-muscular coordination and by assessing the muscular behaviour during various types of dynamic tasks.

This thesis' goal was to quantify the function of the neuromuscular control mechanism in terms of motor output in order to gain a deeper insight into the muscular behaviour and the functional state of muscles that stabilise the knee during dynamic tasks, in general and between individuals. This is achieved by testing the hypotheses (i) that the spectra of EMG recordings from sprint- and endurance-trained athletes were sufficiently different to allow assigning an athlete to one of the groups, (ii) that the EMG signal combined with a time-frequency analysis is sufficiently sensitive to detect a synchronisation, thus a correlation of intensity waveforms, (iii) that the neuromuscular control uses a temporal raster and (iv) that dominant neuromuscular activation strategies exist that are used by different subjects.

Outline of this Thesis

This thesis's content is divided into four chapters that are organised in the following structure:

Chapter 2 addresses the first research question, namely: Is it possible to distinguish the EMG signal, i.e. MF and EMG frequency spectrum, of endurance-trained athletes from those of sprint-trained athletes recorded during isokinetic knee extension by using a non-linearly scaled wavelet transform [105]?

There is significant evidence showing that the EMG signal of a muscle mirrors the anatomical, physiological and biochemical properties of the underlying muscle [26, 123]. Therefore, consistent differences in the EMG spectra between the two groups were expected because of the differences in the muscle features resulting from the various training regimes by applying pattern recognition methods. To our knowledge we were the first ones, who had applied both spherical classification and support vector machine to EMG frequency spectra extracted from wavelet-transformed EMG signals before 2010.

Therefore, this chapter shows the first results of a wavelet-based EMG classification to determine spectral changes in muscle activity due to various training regimes.

Chapter 3 details the adaptable nature of human muscle activity by focusing on the inter- and intra-muscular coordination and the muscular behaviour in healthy females, while level walking.

Recently, neuromuscular control mechanisms, found in wavelet-transformed EMG signals [105], have shown both rhythmicity between 25 to 55 Hz and a tight control of muscle activity in running as well as in maximal contracted muscles [92, 109]. In Chapter 2 (Fig. 1), rhythmicity has been spread in regular time intervals of 80 ms over the duration from 60° to 30° knee extension. These visual considerations, the alternation between high (dark spots) and low (light spots) intensities were quantified while walking in Chapter 3.

The study in Chapter 3 was performed to enhance the knowledge about the precision of muscle activity patterns plus the rhythmicity of muscular events (i) between muscles, (ii) within any muscles and (iii) between individuals while walking in the time period between 200 ms before and 200 ms after heel strike. Furthermore, the EMG signals of two additional electrodes next to the original electrode position were measured. This approach aimed to improve spatial and temporal information from a larger part of the muscle.

Chapter 4 explores the neuromuscular control strategies in the period from 200 ms before to 200 ms after heel strike within thigh muscles, while level walking. In this chapter, the same EMG signals of healthy females were analysed as included in Chapter 3. A PCA approach was applied on wavelet-based EMG signals [105] of individual muscles to determine the intra-muscular coordination. Therefore, the study was performed to identify dominant neuromuscular activation strategies used by different subjects while walking. To our knowledge, there have been no published reports, which have described the use of PCA on wavelet-based EMG signals to identify the neuromuscular control strategies within any muscle.

Chapter 5 is the last chapter in this thesis and concludes the thesis with a general discussion. It summarises the main contributions of this research and discusses comments on the experimental methods. Further, it lays out some suggestions for future work.

As this thesis is based on independent manuscripts, there is some repetition particular in the methods and introduction sections of this thesis.

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Chapter 2

The Effect of Sprint and Endurance Training on Electromyogram Signal Analysis by Wavelets

An adapted version of this chapter has been published as: C. Huber, B. Göpfert, PF-X. Kugler and V. von Tscharner. The effect of sprint and endurance training on electromyogram signal analysis by wavelets. *J Strength Cond Res* 24(6): 1527-1536, 2010.

The purpose of this study was to relate the spectral changes of surface electromyograms (EMGs) to training regimes. The EMGs of *M. vastus medialis* and *M. vastus lateralis* of eight female sprint-trained (ST) and seven female endurance-trained (ET) athletes were examined, while performing isokinetic knee extension on a dynamometer under four different loading conditions (varied angular velocity and load). The EMG signals were wavelet-transformed and the corresponding spectra were classified, using a spherical classification, support vector machine (SVM) and mean frequency. Consistent differences in the EMG spectra between the two groups were expected because of the difference in the muscle features resulting from the various training regimes. On average, the ST athletes showed a downshift in the EMG spectra compared with the ET athletes. The spectra of the ST and ET athletes were classifiable by spherical classification and SVM, but not by the mean frequency. Therefore, the different shapes of the EMG spectra contained the information for the classification. The hypothesis that the specific muscle differences caused by various training regimes are consistent and lead to systematic changes in the surface EMG spectra was confirmed. In the near future, with the availability of new apparels, ones with integrated EMG electrodes, a measurement of the EMG will be available to coaches more frequently. The classification of wavelet transformed EMGs will allow monitoring training-related spectral changes.

Key words: *isokinetic knee extension, EMG spectra, wavelet analysis, pattern recognition, classification, apparels.*

ABBREVIATIONS

cf, centre frequency; *CV*, conduction velocity; *EMG*, electromyography; *ET*, endurance-trained; *MF*, mean frequency; *MU*, motor unit; *MUAP*, motor unit action potential; *MUAPt*, motor unit action potential translates to a shape in time; *ST*, sprint-trained; *SVM*, support vector machine; *VL*, M. vastus lateralis; *VM*, M. vastus medialis.

INTRODUCTION

Muscle properties are known to change with training. For example, properties such as diameter and fibre-type distribution do change [27]. In a study on endurance-trained (ET) athletes such as marathon runners, the relative type I muscle fibre percentage was higher than in sprint-trained (ST) athletes [22]. A high-velocity isokinetic strength training resulted in an increase of the cross-sectional area of the elbow flexors [25] and marathon training increased the cross-sectional area of *M. gastrocnemius lateralis* [27]. These changes of muscle properties are reflected in the spectra of an electromyogram (EMG). A study of Wakeling et al. [34] on fish explained that fast twitch fibres generally have a higher mean frequency (MF) than slow twitch fibres. Von Tscharner and Nigg [33] concluded that the EMG spectra – among other aspects – reflected the task-specific selection of muscle fibres. For example, the muscle tuning of *M. tibialis anterior* before heel strike resulted in the expression of higher frequencies in the EMG signal than those observed after heel strike [32]. One can therefore expect that training by using fast or slow movements could affect the distribution of muscle properties that generate high and low frequency components in the EMG spectra.

There are two interesting questions: First, “Can one use the spectra to assess whether an athlete did speed or endurance training?” and secondly, “What can one deduce from the spectra about the muscle properties?” The present study primarily addresses the first question, because this may lead to practical applications such as following training results of athletes or assessing their predisposition. Nevertheless, the second question may yield further insight in a controversial interpretation of EMG spectra. The controversial interpretation has recently been debated in a point-counterpoint article [7, 33]. The authors summarised the properties of the muscles, which generate and affect the EMG spectra. The point was “Spectral properties of the surface EMG can characterize motor unit recruitment strategies and muscle fiber type” [33]. According to the “point”, the spectral differences should allow the classification of ST or else ET athletes.

To interpret the frequency changes, one has to be aware that the spectrum of an EMG is primarily determined by the shapes of the motor unit (MU) action potentials (MUAPs) as generated along the muscle. So a MUAP in turn translates to a shape in time (MUAPt) that is observed by the measuring device at a fixed position. The translation from MUAPs to MUAPt results from the conduction velocity (CV) [18]. An interference EMG is generated by a superposition of the different MUAPts. The training type may change many of the muscle properties, especially properties, which change the size of the muscle, its composition and the neuromuscular control. Yet, most frequently, discussions were boiled down to changes of CV that subsequently alter the MF of the spectra. Among other factors, the CV is influenced by the type [8], the proportion [22] and the cross-sectional area of the muscle fibre [17]. On the other hand, Troni et al. [28] explained that the CVs were almost normally distributed and formed a single peak, and thus, contained not much of a detailed structure. Therefore, one has to consider that fibre-type, proportion and cross-sectional area also change the shape of the MUAP, and hence, the spectra. Farina et al. [9] commented on various reasons for changing the MF of the EMG spectra. In a study on *M. abductor pollicis brevis*, it was clearly shown that beside changes of CVs, the shape of the spectra also changed with fatigue [1], thus indicating changes in the shape of the MUAP. One of the factors which strongly determine the shape and the size of the MUAP is the endplate distribution in the innervation zone. The area of the innervation zone [26] stands for a primary component affecting the shape of the MUAP and so the spectra. During the athletes’ training, all the features of the muscle may somehow change. Because of this, it can be expected that the spectra of ST and ET athletes will be of different shapes. The question remains, whether these different shapes are consistently different and allow the assessment of the training status.

In many studies, the assessment of spectral differences has been reduced to measuring the MF (e.g. [13, 21]). Nevertheless, different spectral shapes resulting from altered MUAP can't be represented by a single variable. These spectral differences are expected to be very subtle, if the groups comprise non-injured athletes. To be able to discuss the spectral differences recorded for two different groups, the EMG spectra have to be characteristic for the training of the groups. A pattern recognition method has to be applied to the spectra to decide, whether they correlate with a training regime. These days, very complex pattern recognition methods are available [2, 5, 6, 10]; one of them, the spherical classification, was previously applied to EMG signals [16, 30]. Classification is not necessarily possible by using one muscle at a time. Muscles work in concert and consequently, multiple muscles were included for classification purposes [31]. As the theory of classification evolves, the selected methods have to be carefully evaluated against one another. In a number of cases, a projection to higher dimensional spaces leads to a linear classification of the samples, while in other cases, a dimensionality reduction is more appropriate. Some propositions have been made for the classification of EMGs [19].

The purpose of this study was to test the hypothesis that the spectra of EMG recordings of female athletes, which were trained for sprinting (ST athletes) or endurance tasks (ET athletes) were adequately different to allow assigning an athlete to one of the group. Especially, the spectral differences in *M. vastus lateralis* (VL) und *M. vastus medialis* (VM) resulting from the different training regimes were of interest for the four different loading conditions. It was hypothesised that the differences become classifiable through using a non-linearly scaled wavelet analysis of the EMG signals [29] combined with a spherical classification method [30] or a support vector machine (SVM) [3]. Both methods have been recently developed and were – to our knowledge – not previously applied to EMG signals. They are important because new apparels with integrated EMG electrodes become available to athletes. Yet, the analysis methods that yield relevant information for coaches have not yet been sufficiently developed. It is important to validate and discuss new analysis methods, which will enable the coaches to deduce from EMGs whether the training resulted in an EMG that is typical for the training regimes.

METHOD

Experimental Approach

This study was designed to address the question of how endurance and sprint training affect the muscle activity during knee extension.

Subjects

Athletes, who trained by fast movements, for example, sprinters and bobsleigh pushers, were referred to as ST athletes, while marathon runners and triathletes were referred to as ET athletes. Eight female ST athletes (mean ± *SD* age = 24.1 ± 3.5 years; mean ± *SD* height = 1.71 ± 0.07 m; mean ± *SD* mass = 65.7 ± 8.8 kg) and seven female ET athletes (mean ± *SD* age = 26.7 ± 5.0 years; mean ± *SD* height = 169.9 ± 4.0 cm; mean ± *SD* mass = 57.0 ± 5.4 kg) volunteered for this study. The ST and ET athletes were in the Swiss national top 15 of their sport and age group and were training for the winter season competitions (December 2006 to early March 2007). All of them had at least four years experience in participating in competitions. The ST group consisted of athletes from track and field (100 m and 100-m hurdles) plus athletes of the Swiss national world cup team in bobsleigh. The ET athletes were either runners on the track (distances longer than 1'500 m), or road runners (triathletes and marathon runners). The inclusion criterion for all athletes was that they had no previous knee or leg injury.

The investigation was approved by the official Ethics Committee. Subjects were informed of the experimental risks and signed an informed consent document prior to the investigation. All athletes confided their age and dominant leg side, and their height and weight were measured.

Study Design

The measurements were made on a hydraulic isokinetic dynamometer of type Cybex Orthotron KT 2 (Cybex, Medway, MA, USA). The athletes were seated with flexed legs on the dynamometer with a hip flexion angle of 100°. The trunk and both thighs were fixed with belts to minimise muscular compensation and evasive moments. The two knee adapters were fixed at half the distance from the fibula head to the lateral maleoli. The athletes executed knee extensions under four different conditions (Table 1): (a) velocity > 105 °/s and load < 27 N·m, (b) velocity > 105 °/s and load > 50 N·m, (c) velocity < 32 °/s and load < 27 N·m and (d) velocity < 32 °/s and load >50 N·m. For each condition, the subjects performed eight trials, starting with condition #1 and finishing with condition #4, all the way through a movement range of 90° knee extension (start and end knee angles were 90° and 0°, respectively). Bad trials were repeated if the load output and angular velocity was not within the range of the requested condition. One ET athlete was unable to reach the load level under the given angular velocity in condition #2. The ET group consists only of six ET athletes, who have fulfilled condition #2. For further analysis, the five trials closest to the median value (Table 1) were used, hence, minimising the effects of outliers. The knee extension from 60° to 30° was employed.

TABLE 1. Angular velocity and load range for condition #1 to #4.

Condition	#1	#2	#3	#4
Angular velocity	High	High	Low	Low
Load level	Small	Heavy	Small	Heavy
Angular velocity (°/s)	[105.6-263.2]	[100.7-180.7]	[12.8-32.0]	[8.2-32.4]
Load level (N·m)	[9.0-26.9]	[50.8-94.3]	[5.4-20.9]	[50.2-89.7]

Data Recording

Kinematic and kinetic signals of the knee were simultaneously measured by using the following equipment: goniometer (LOB^2, Basel, Switzerland) for measuring knee angle over time, acceleration sensor (Biovision, Wehrheim, Germany) for controlling dynamometer angle and torque sensor (Cybex, Medway, MA, USA) for measuring torque over time in the knee and in the dynamometer axe. Afterwards, the kinematic and kinetic signals were smoothed with a 50 Hz low-pass Butterworth filter (4th order) and resampled at 500 Hz.

The muscle activity of VL and VM were measured on the dominant leg side, using an EMG system (Biovision, Wehrheim, Germany). The placement of the bipolar Ag/AgCl surface electrodes with a diameter of 10 mm and an inter-electrode distance of 22 mm (Noraxon U.S.A Inc., Scottsdale, AZ, USA) were in accordance with the SENIAM-recommendations [14]. The reference electrode was placed on the tibial tuberosity of the dominant leg. All electrodes were connected to single differential amplifiers with a band path of 10-700 Hz (Biovision, Wehrheim, Germany). The EMG was sampled at 2'520 Hz using a DAQ-Card (DAQ-Card-6036E, National Instruments Corporation, Austin, TX, USA) and saved on a laptop computer.

Data Processing

Wavelet Transform

The EMG signals were submitted to a time-frequency analysis described by von Tscharner [29]. This analysis method consists of a filter bank of 14 non-linearly scaled wavelets (Cauchy wavelets) indexed by j. Each EMG signal was filtered by these wavelets, which were characterised by their centre frequency (cf_j) (7, 19, 38, 62, 92, 128, 170, 218, 272, 331, 395, 457, 542 and 624 Hz). The wavelets were abbreviated as, for example, $w_{457\mathrm{Hz}}$ indicating that this wavelet had a centre frequency of 457 Hz. The bandwidth of the filter and the time resolution was computed previously [29]. The EMG signal was convolved by these wavelets yielding an intensity $p_{j,n}$, where n represents the index for the time points. The intensity of $w_{7\mathrm{Hz}}$ wasn't further considered, because it is most likely affected by movement artefacts [4]. The intensity $p_{j,n}$ is proportional to the EMG power within the frequency band. The magnitude of an intensity pattern is the square root of the sum of all squared intensities. During the wavelet transformation, the data were resampled at 500 Hz. The results $p_{j,n}$ were visualised as EMG intensity patterns by showing contour plots, where the abscissa represents time, the ordinate shows the frequency and the contours and grey shades stands for the intensity.

Electromyogram wavelet spectra were used to monitor changes in the MU properties resulting from the training. To obtain representative spectra, an averaging procedure was used. The average of the wavelet spectra obtained for the movement range of 60° to 30° knee extension was called the spectral vector (s_vector) of an intensity pattern. All s_vectors were normalised to total power of 1 by dividing the s_vector through the sum of its components. So for each athlete indexed by k and condition, a mean_s_vector was computed by building the average of the five s_vectors. To use the mean_s_vectors for classification purposes, only a limited range containing the information is required – and the data have to be appropriately rearranged. The power of the mean_s_vectors of $w_{\text{start Hz}}$ up to $w_{\text{end Hz}}$ of VL and VM were stacked on top of each other to form one long vector. After that, the range of frequencies (start to end) was selected based on the results later shown. These vectors were arranged as columns in a matrix W_{ST} and W_{ET}, respectively.

The group mean across the subjects was computed for W_{ST} and W_{ET}. Moreover, the group mean spectra were visually inspected. Two spectra were considered to have different shapes if they couldn't be brought to superposition by normalisation and rescaling of the frequency axis. There were four matrices for W_{ST} and W_{ET} representing the spectra of the four conditions. These matrices were used as input to the classification methods (spherical classification, SVM classification and MF classification).

Pattern Recognition Methods

The spherical classification of the wavelet transformed EMG intensity pattern was presented previously by von Tscharner [30]. The spherical classification was described in general [10]. In this study, the spherical classification of von Tscharner [30] was adapted to the EMG spectra, while the vector 'g' represents the distances of a mean_s_spectra to the midpoint of the shell of each of the spheres. If $g_{\text{ST},k}$ is larger than $g_{\text{ET},k}$, then athlete k belongs to the ST group, otherwise to the ET group. This assignment criterion was used to assess separability and classification. A crossvalidation was done through a leave-one-out method [10, 30]. In the leave-one-out method, one subject, the one left out, was used as a new test subject and eliminated from the W_{ST} and W_{ET}. The separability was computed for the subjects in the reduced W_{ST} and W_{ET}, whereas the classification of the test subject was performed using the spheres obtained from the reduced W_{ST} and W_{ET}. What's more, this procedure was repeated, using each subject once as a test subject. Therefore, for each subject, one gets to know (i) whether she was correctly assigned to the correct group (classifiable) and (ii) the separability of the remaining subjects that were used as controls. The final result of the crossvalidation was (i) the average separability of each of these tests and (ii) the crossvalidation rate (number of classifiable test subjects divided by the total number of subjects). To visualise the spherical classification process, the distances $|g_{\text{ST},k}|$ and $|g_{\text{ET},k}|$ were plotted against each other. A 45° diagonal line separated the two groups. If there is 100% separability, the two groups appeared on each side of the diagonal line.

Support vector machines have attracted great attention over the last decade [11]. The SVM software was downloaded as freeware from the internet [3]. In the SVM, one still has to decide which kernel to use and there is an adjustable parameter C that controls the performance of classification. We selected a linear kernel and tested C values between 1 and 1'000. A C value of 50 was selected as an educated guess by an experienced user. The W matrices were used as input to the SVM. The same crossvalidation using the leave-one-out method described above was used. The results were, as for the spherical classification, the average separability and the crossvalidation rate.

In the more classical EMG analysis, the MF was used as a measure of spectral differences. The group MF for the different muscles was computed for the classical comparisons. The purpose of this study requires a classification of an athlete as belonging to the ST or ET group. The following classification method based on MF was used. The MFs for the group mean of W_{ST} and W_{ET} were computed for each condition as a weighted average of the centre frequencies. Hence, two MFs were obtained, one for VL, MF_{VL}, the other for VM, MF_{VM}. A subject was deemed correctly assigned to its group if both, MF_{VL} and MF_{VM}, were closer to their respective group mean. Some subjects weren't assignable because both MFs were not simultaneously closer to their respective means. A crossvalidation using the leave-one-out method was used to compute the crossvalidation rate of the assignable subjects and the overall crossvalidation rate. In this case, the group means of MF_{VL} and MF_{VM} of the control subjects didn't contain the MF_{VL} and MF_{VM} of the subject that was left out to be tested. The result of the crossvalidation for MF were (i) the rounded average assignable control subjects, (ii) the average separability (correctly assigned control subjects divided by the assignable control subjects), (iii) the assignable test subjects, (iv) the crossvalidation rate (classifiable test subjects divided by average assignable subjects) as well as (v) the overall crossvalidation rate (classifiable test subjects divided by number of subjects). The overall crossvalidation rate corresponds to the product of the prior probability of a subject being assignable with the probability being assigned to the correct group (crossvalidation rate).

All signal processing was performed using programs written in the Matlab programming software (MathWorks, Version R2007a, Natick, MA, USA).

Statistical Analyses

The statistical analyses typical for pattern recognition methods were applied. In a high-dimensional vector space, one can often obtain perfect separability (100%) by a discriminant. Yet, a new subject isn't necessarily assigned to the correct group by this discriminant. A correctly assigned new subject was called classifiable. A leave-one-out crossvalidation procedure [10] was used to obtain the crossvalidation rate (classifiable subjects divided by total subjects) that indicates the probability of correctly assigning an unknown subject to the ST or ET group. If the assignment would be random, one would acquire a 50% crossvalidation rate. A binomial test with equal probability for the two conditions (belonging to group #1 or group #2) was used to determine the statistical significance of the classifiable subjects and thus of the crossvalidation rate. The computed one sided p value indicated the cumulative probability of getting a number of classifiable subjects greater or equal to the reported classification as a result of random assignments. If the p value was below 0.05, then the hypothesis that the classification was a result caused by random assignments can be rejected and thus, the crossvalidation rate was deemed significant.

The binomial test was applied to the crossvalidation rate of all three classification methods. Whether the mean of the MF of the two groups were significantly different was irrelevant for the classification. However, because the MF was one of the most important variables in the past, the group differences for the MF variables were analysed with an unpaired Student t-test with Microsoft Excel 2002 (Microsoft Inc., Redmond, WA, USA).

RESULTS

Typical intensity patterns for ST and ET athletes are shown in Figure 1A-B, respectively. These patterns were recorded for the movement range of 60° to 30° knee extension for VL. These examples were recorded for condition #3, thus representing low angular velocity and small load. The patterns showed a series of muscle activities that were spread over the duration of the movement. They seem to be arranged in regular time intervals of about 80 ms. These typical repetitive muscle activities can be found in both muscles of all subjects, irrespective of the condition. The patterns were so variable that one could not visually assign them to one or the other condition. The spectra in the range 60° to 50° and in the range 40° to 30° knee extension indicated that there was a slight frequency increase with the knee angle (results not shown). The increases are small enough that the following analysis could be limited to the mean spectra recorded over the full range of 60° to 30° knee extension. These spectra were normalised to a total power of 1.

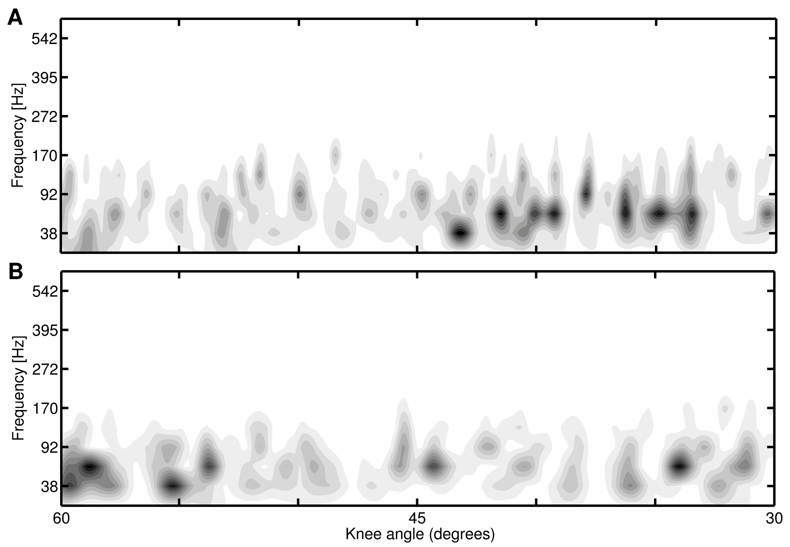

FIGURE 1. EMG intensity patterns of (A) a sprint- and (B) an endurance-trained athlete for 60° to 30° knee extension for M. vastus lateralis and condition #3. White indicates low intensity, black highest intensity.

The averaged normalised EMG wavelet spectra of VL and VM were shown in Figure 2 for each condition for the ST group (solid lines) and the ET group (dashed lines). The visual assessment of the spectra between the two groups showed that significant power was only observed up to $w_{170\text{Hz}}$. In general, although not for spectra of VL in Figure 2D, the spectra of both groups revealed a different shape. As a matter of fact, higher proportions of the lower frequency components can be seen for the ST group. The detailed analysis showed that the average MF_{VM} was significantly higher in the ET group than in the ST group, while the average MF_{VL} showed the same trend, but wasn't significantly different (Table 2). Whether the visually observed differences in the shape of the spectra contained enough information to decide about the training status of the athletes had to be assessed numerically.

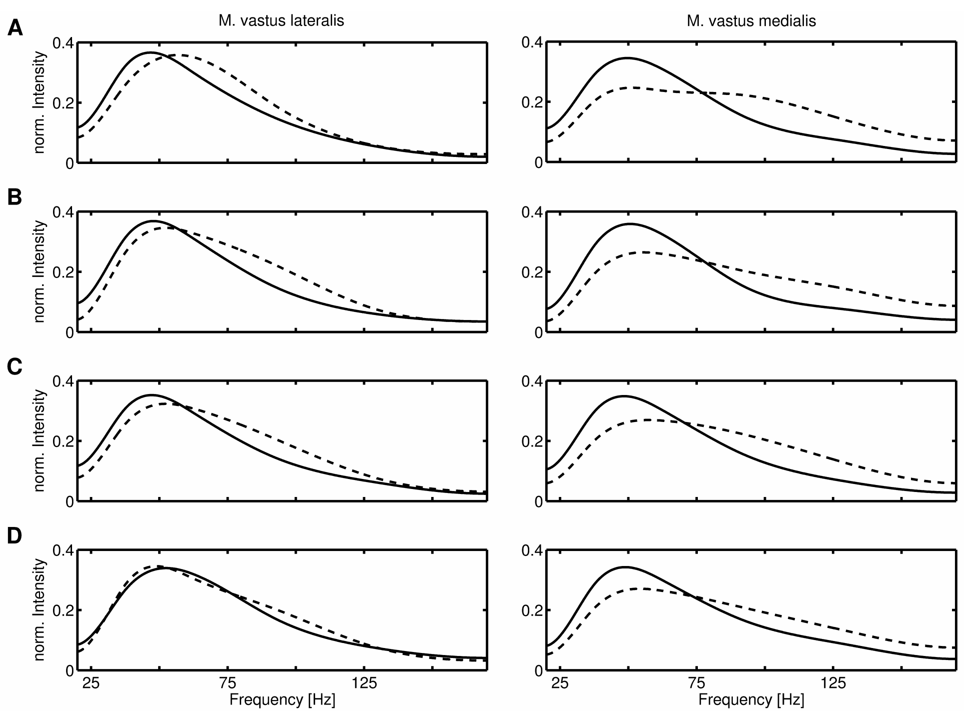

FIGURE 2. Normalised mean EMG frequency spectra of M. vastus lateralis (left) and M. vastus medialis (right) (interpolation of the centre frequency cf_j by a cubic spline) for the sprint- (solid lines) and endurance-trained group (dashed lines) for (A) condition #1, (B) condition #2, (C) condition #3 and (D) condition #4.

TABLE 2. Mean frequencies for condition #1 to #4.

Condition	#1	#2	#3	#4
Number of subjects	15	14	15	15
		M. vastus lateralis (MF *(SE)* [Hz])		
ST	62.86 (3.31)	67.11 (5.08)	66.80 (3.32)	72.66 (4.51)
ET	69.03 (2.40)	75.23 (4.82)	75.27 (2.65)	73.04 (1.47)
p value of t-test	0.16	0.27	0.07	0.94
		M. vastus medialis (MF (SE) [Hz])		
ST	67.65 (4.11)	72.86 (6.53)	69.72 (3.28)	73.58 (5.92)
ET	89.19 (3.15)	96.20 (4.17)	88.92 (3.56)	89.65 (2.50)
p value of t-test	0.001*	0.01*	0.002*	0.03*

ET = endurance-trained; MF = mean frequency; SE = standard error; ST = sprint-trained.
*Significant different mean frequency between the two groups ($p < 0.05$).

The three possible classification methods, spherical classification, SVM classification and MF classification yielded the following results. The separability of the spectra obtained by the spherical classification method was shown for condition #1 in Figure 3. The ST subjects (black dots) have a smaller distance from the shell centre of their group and are therefore located closer to the ordinate. The ET subjects (grey triangles) have a smaller distance from the shell centre of their group and are therefore located closer to the abscissa. The 45° diagonal line represents the line separating the two groups. The spherical classification indicated that the spectra of the athletes of the two groups were over 83% separable and over 73% classifiable for unknown subjects as shown in Table 3. According to a binomial test, there was a significant classification as indicated by the *p* values of the crossvalidation rate for the conditions #1 to #3. For condition #4, there were 11 classifiable subjects, which was a similar absolute number than for the other conditions. But according to Fukunaga [10], the spherical classification doesn't automatically lead to the absolute best classification. Hence, the results had to be compared, using mathematically more demanding methods.

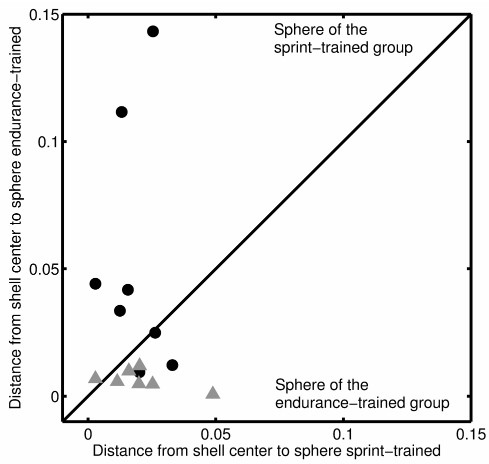

FIGURE 3. Example of the separability of the normalised mean electromyogram wavelet spectra of the sprint- (black dots) and endurance-trained (grey triangles) group for condition #1 using the spherical classification in combination of a leave-one-out crossvalidation. The 45° diagonal line represents the line separating the two groups.

TABLE 3. Results of the spherical separation and classification for condition #1 to #4.

Condition	#1	#2	#3	#4
Number of subjects	15	14	15	15
Average separability (%)	90.5	87.4	99.5	83.3
Classifiable	12	11	12	11
Crossvalidation rate (%)	80*	78.6*	80*	73.3
p value of crossvalidation rate	0.02	0.03	0.02	0.06

*Significant crossvalidation rate ($p < 0.05$). The classification was done by the leave-one-out method.

TABLE 4. Results of the support vector machine classification for condition #1 to #4.

Condition	#1	#2	#3	#4
Number of subjects	15	14	15	15
Average separability (%)	100	100	100	100
Classifiable	14	10	14	14
Crossvalidation rate (%)	93.3*	71.4	93.3*	93.3*
p value of crossvalidation rate	0.0005	0.09	0.0005	0.0005

*Significant crossvalidation rate ($p < 0.05$). The classification was done by the leave-one-out method.

The SVM indicated that the spectra of the athletes of the two groups were 100% separable as shown in Table 4. The crossvalidation rate was between 71% and 93% for the classification of unknown subjects. The results of the SVM were for all conditions except for condition #2 higher than for the spherical classification. Reanalysis of the data without subject #14 altered the cross-validation rate of condition #2 from 71% to 93%. These results are not shown in Table 4. Thus, subject #14 most likely represented an outlier.

TABLE 5. Results of the mean frequency classification for condition #1 to #4.

Condition	#1	#2	#3	#4
Number of subjects	15	14	15	15
Average assignable (rounded)	11	10	13	8
Average separability (%)	84	90	90	85
Assignable test subjects	10	10	13	4
Classifiable test subjects	8	9	11	3
Crossvalidation rate (%)	73	90*	85*	38
p value of crossvalidation rate	0.11	0.01	0.01	0.85
Overall crossvalidation rate (%)	53	64	73†	20
p value of overall crossvalidation rate	0.50	0.21	0.06	0.99

*Significant crossvalidation rate. †Significant overall crossvalidation rate ($p < 0.05$). The classification was done by the leave-one-out method.

The classification based on MFs was more cumbersome because only a limited number of subjects could be assigned to one or the other group (Table 5). In contrast to the spherical classification and the SVM classification, there was one-quarter of the cases (subject and condition) not assignable. The analyses of those subjects that were assignable yielded a crossvalidation rate that was significant for two conditions only. Yet, the overall crossvalidation rate indicated that the subjects were either not assignable or miss-assigned were very large. Additionally, considering the *p* values of the overall crossvalidation rate, an assignment of an unknown subject based on MF wasn't reliable.

DISCUSSION

Our results confirmed the hypothesis that specific muscle differences caused by various training regimes in sprinting and running, are reflected in systematic differences in the surface EMG spectra, when a filter bank of non-linearly scaled wavelets was used to extract them. Furthermore, these differences were sufficiently distinct to allow detecting, if an athlete has been trained for a sprinting or an endurance task, irrespective of the details of the training regime. Nevertheless, the isometric EMG measurements published by various researchers (e.g. [21]) couldn't explain the spectral changes that we observed during dynamic movements. Yet, different kinds of dynamic movements do change the muscle features as discussed below. Shepstone et al. [25] measured a larger diameter in the muscle fibres after a fast strength training for both the type I and type II muscle fibres. According to classical EMG theory, larger fibre diameter should lead to higher CV [17] and shifts to higher frequencies were experimentally confirmed [12]. What's more, these results were obtained for isometric contractions, using a force that corresponded to 70% of maximal voluntary contraction. Based on these two relationships, increase of fibre diameter for ST athletes and increase in CV, one would expect that ST athletes would have higher MFs in their spectra. However, our results showed on average lower MFs for the ST athletes than for the ET athletes (Table 2). According to these results, one would be inclined to conclude that the usual explanation of the relationship between fibre-type, CV and frequency are not sufficiently understood to explain the results. However, the present results are – in accordance with studies that showed that even though the CV did change, the MF didn't [8]. In some cases, the MF was independent of the fibre diameter [34]. One might argue that the basic relationships were usually measured during nondynamic loading conditions. So it could be that sprint training has increased the ability to synchronise the MUAP, and hence, decreasing the MF. It isn't known under what circumstances the synchronisation increases. Like stated before, the riddle can only be solved by measuring the EMG spectra and the CV at the same time [7, 33]. These inconsistencies may suggest that the spectra may not be characteristic for the trained task. Still, our results clearly showed that the spectra were sufficiently consistent to be able in most cases to correctly assign an unknown EMG spectrum to the ST or ET group through using a spherical classification or SVM classification. For a correct classification, the information contained in the whole spectra was relevant, while the MF didn't have enough information. So the information was therefore contained in the shape of the spectra. These shapes were visibly different for the two groups, as shown in Figure 2. So the differences can't be explained by a change in CV only. The detection of differences in shape required using pattern recognition methods. The advantage of using the spherical classification was its simplicity. The advantage of the SVM – as long as one only considers a linear kernel and an appropriate value of C – is that it might, in future, also reveal which part of the spectra contained the information required for the classification.

The shape of the spectra depends on the recruitment of the selected MUs (central control) and on the peripheral build-up of the interference EMG. A high correlation of MUs can be also described as synchronisation [15]. Semmler and Nordstrom [24] could prove that strength-trained athletes had a greater degree of synchronisation of MU than untrained subjects. The higher the synchronisation of MUs, the more muscle fibres became activated. This helped in performing a fast force production [23], like that needed in sprinting, where muscles have to work in concert. Synchronisation of MU "leads to an absolute increase of power in the EMG spectra at lower frequencies and to a relative decrease of power at high frequencies" [35]. But synchronisation also results in a downshift of the MF [15]. These findings are in contrast to the increase in MF during isometric contractions observed for many years [18]. It is often supposed that during isometric contractions performed at maximum voluntary contraction, all muscle fibres will be activated. Yet, in dynamic conditions, spectral changes can result from specifically selected muscle fibres during the actual movement of the performing athlete. The selected muscle fibres strongly depend on their availability. Muscle biopsies indicate, which fibres are available and how the proportion changes over the training period [27]. They don't reflect the immediate selection of fibres. Even if we won't be able to explain and fully understand the details behind the spectra, this work clearly shows that the spectra changed in a systematic way and therefore they contain practical reliable information about the training of the athlete. One can therefore conclude that an EMG spectrum recorded during a dynamic sports movement yields its own information about the muscle condition in addition to the information obtained by EMG spectra recorded for isometric contractions or muscle biopsies. The analysis of the condition of muscles will become a multifactorial task.

PRACTICAL APPLICATIONS

The coaches would always like to know, if an athlete's muscle response is in accordance to the chosen training regime, as well as whether an athlete has reached the optimal muscular adaptation. The athletes would like to optimally tune their muscles for the competition to gain an advantage over the other competing athletes because it is known that the tuning of muscular system can be actively influenced [20]. With the availability of new apparels, one with integrated EMG electrodes, a measurement of the EMG will be available to coaches more frequently in the near future. This work shows that the classical analysis of an EMG, based on MFs, isn't able to assess the training status of an athlete. Because of this, it was therefore important to develop, validate and discuss alternative analysis methods. The new wavelet based methods that are currently tested, represent such analysis methods. In combination with the newest pattern recognition methods it allows the classification of the wavelet EMG spectra that result from different trainings regimes and levels.

The interpretation of the results indicates that ST athletes may improve the ability to synchronise their muscle activation. Through the better synchronisation, the movement might be more precise and so, less energy is used for adjustments. One can assume that the training of fast movements and synchronisation helps improving the energy efficiency in normal tasks.

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Chapter 3

Muscular Timing and Inter-Muscular Coordination in Healthy Females While Walking

The dynamic interplay between muscles surrounding the knee joint, the central nervous system and external factors require a control strategy to generate and stabilise the preferred gait pattern. Moreover, the electromyographic (EMG) signal is a common measure, reflecting the neuromuscular control strategies during dynamic tasks. Neuromuscular control mechanisms, found in processed EMG signals, showed a precise pacing with a pacing rhythm, a tight control of muscle activity in running and in maximally contracted muscles. The purpose of this study was to provide an insight how muscles get activated during walking. The EMG power, extracted by the wavelet transform (92–395 Hz), over a time period encompassing 200 ms before and 200 ms after heel strike was analysed. The study showed that the wavelet-based analysis of EMG signals was sufficiently sensitive to detect a synchronisation of the activation of thigh muscles while walking. The results within each single subject and within the group consisting of ten healthy females showed that, although there was a lot of jitter in the locations of the intensity peaks, the muscle activation is controlled, on average, by a neuromuscular activity paced at about 40 ms, but with variable amplitudes. Despite the jitter of the signal, the results resolved the temporal dependency of intensity peaks within muscles surrounding the knee and provided an insight into neural control of locomotion. The methodology to assess the stabilising muscle activation pattern may provide a way to discriminate subjects with normal gait pattern from those with a deteriorated neuromuscular control strategy.

Key words: *thigh muscles, gait, EMG, wavelet analysis, rhythmicity.*

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ABBREVIATIONS

BF, M. biceps femoris; *EMG*, electromyography; *HAM*, hamstring muscle group; *QF,* Mm. quadriceps femoris; *RF*, M. rectus femoris; *ST*, *M.* semitendinosus; *VL*, M. vastus lateralis; *VM*, M. vastus medialis.

INTRODUCTION

The knee is a complex joint with many muscles that have to be controlled by the neuromuscular control mechanism. The dynamic interplay between these muscles, the central nervous system as well as the external factors require a control strategy to generate and stabilise the preferred gait pattern. Many studies have shown that small changes in external factors, for instance different shoes, don't change the preferred movement [25]. Yet, to stabilise a preferred movement the neuromuscular control system must be very flexible. The stabilising neuromuscular control strategy applied while walking can be observed by monitoring the muscle activity using electromyography (EMG) as an indicator.

The EMG signal is a common measure, reflecting the neuromuscular control strategies during dynamic tasks [7, 8, 12, 28, 38, 40, 41]. Neuromuscular control mechanisms, found in processed EMG signals, showed a precise pacing with a pacing rhythm [3, 4, 29-32, 34, 35]. Additionally, works done in the late 1990s revealed that these rhythms are correlated to the activity of the motor cortex and can so be considered as the result of the activity of the central nervous system [4]. However, the studies revealing the corticomuscular interaction usually did not explicitly resolve the pacing in the EMG signal. In maximally activated muscles [34, 35] and muscle activities measured while running [31], the rhythms were explicitly resolved and showed a tight control of muscle activity. Because of this, the presence of rhythmicity within a longer lasting muscular event indicates that there is a kind of programmed function controlled by a neuromuscular activity [1].

The musculoskeletal mechanics of gait depends on mono- and biarticular muscles, which are activated in a specific sequence. Especially at heel strike, where the human locomotor system is affected by irregular impact forces, controlled muscle activation strategies are essential for counteracting the destabilising forces. A coordinated activity of *Mm. quadriceps femoris* (QF) is essential to maintain dynamic stability of the patellofemoral joint [20, 22]. Such an active control of the patella by precise coordination between *M. vastus medialis* (VM) and *M. vastus lateralis* (VL) is more important, the more extended the knee joint is [21], as occurring at heel strike. Consequently as the foot touches the ground, the muscles have to be prepared to absorb the impact shock by a muscle tuning [26] to regulate the knee joint stabilisation dynamically [21]. A balanced VM and VL activity is required to control the translation of the patella to prevent their maltracking [6, 20, 27]. Already a time delay of 5 ms in the onset of VM relative to VL alters the patellofemoral joint mechanism [24].

Our hypotheses were: (i) that the EMG signal combined with the wavelet-based analysis of this signal is sufficiently sensitive to detect a synchronisation of the activation of thigh muscles while walking and (ii) that the neuromuscular control uses a similar timing raster, like timing for the synchronisation of muscle activity during gait. The study was designed to investigate, how the muscles are controlled by the neuromuscular system before and after heel strike while walking.

The study should provide insight into muscle activation during a movement that doesn't need absolutely tight control. In decerebrated cats, the gait pattern is still present but not stable [10, 11]. Therefore, we have to consider that human muscles have at least two major functions, one is to provide the energy to sustain the movement, and the other is to keep the movement in line by stabilising the joints. It was previously shown that EMG intensity pattern can discriminate between healthy subjects and subjects suffering from osteoarthritis [37]. Yet, pattern classification did't reveal explicitly the changes in the neuromuscular control strategy. Thus, the important next step is to understand the timing strategy of the neuromuscular control. A methodology to assess the stabilising muscle activation pattern may provide a way to discriminate subjects with a normal gait pattern from those with a deteriorated neuromuscular control strategy.

MATERIALS AND METHODS

Subjects

Ten healthy female volunteers (age: 48 ± 7 years, body mass: 61.1 ± 4.9 kg, height: 1.64 ± 0.05 m) with no history of previous knee or lower extremity surgery, osteoarthritis, neurological, or musculoskeletal disorders participated in this study. They were informed of the experimental risks and signed an informed consent form approved by the local Ethics Committee.

Study Design

An instrumented three-dimensional gait analysis with synchronous measurement of the lower extremity muscle activity during normal gait was performed. The lower body kinematics were recorded at 240 Hz with a six-camera motion capture system (Vicon MX13+, Oxford, UK) using the Helen Hayes model [18]. The subjects walked barefoot at a comfortable, self-selected walking speed along a 10 m walkway within the laboratory. A minimum of 12 valid trials was collected. Afterwards, the time of heel strike was determined from the position of the heel marker. Two steps per trial were extracted. Due to technical problems, mainly movement artefacts, less than 12 trials were available from seven subjects. Nine trials, hence – 18 steps per subject – were used for the calculations. All in all, 180 steps were analysed.

Data Recording

Surface EMG was recorded from muscles of the QF and hamstring (HAM) muscle groups from the right lower limb. The muscles of the QF group were: *M. rectus femoris* (RF), VM and VL, and of the HAM group: *M. semitendinosus* (ST) and *M. biceps femoris* (BF). Bipolar Ag/AgCl surface electrodes (diameter: 10 mm, inter-electrode distance: 22 mm, Noraxon U.S.A. Inc., Scottsdale, AZ, USA) were used. After shaving and cleaning the skin with alcohol according to SENIAM-recommendations [13], three electrode pairs were placed side by side on each muscle, in the direction of the muscle fibres, to get additional spatial and temporal information. The first electrode pair, referred to as original, was positioned according to the SENIAM-recommendations, while the lateral and medial electrode pairs were sideways displaced by 28 mm from the original electrode pair (Fig. 1).

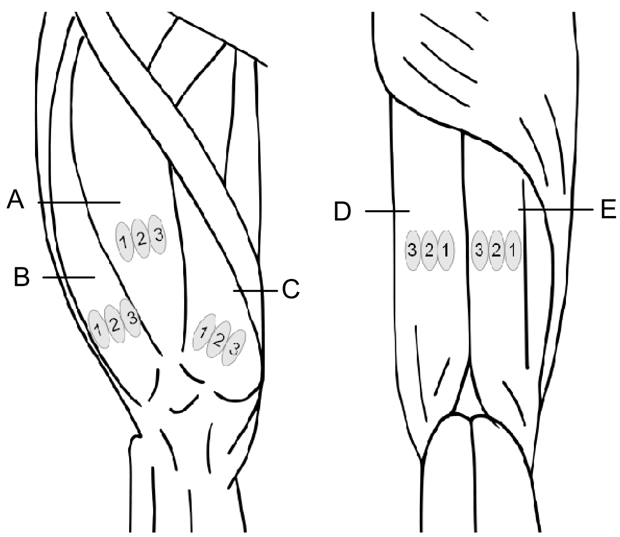

FIGURE 1. Placement of the surface EMG electrode pairs for measuring the activity from (A) M. rectus femoris, (B) M. vastus lateralis, (C) M. vastus medialis, (D) M. semitendinosus and (E) M. biceps femoris is illustrated for the lateral (1), original (2) and medial (3) electrode pairs.

The reference electrode was positioned on the tibial tuberosity. The surface EMG was collected with single differential amplifiers (band path of 10-700 Hz, Biovision, Wehrheim, Germany) at a sampling frequency of 2’400 Hz without further processing. Cables and electrodes were kept in place by an elastic net bandage (Elastofix, Type B, BSN medical GmbH & Co. KG, Hamburg, Germany) that was pulled over the thigh.

Data Processing

Wavelet Transform

The signal analysis was done using a wavelet transform with 13 non-linearly scaled wavelets characterised by their centre frequencies: 7, 19, 38, 62, 92, 128, 170, 218, 272, 331, 395, 457 and 542 Hz [33]. Centre frequencies lower than 92 Hz weren’t considered further because time resolution has to be short enough to detect the rhythm. The theoretical time resolution of the wavelets defined by von Tscharner [33] represents the time difference of two events that occur at the same frequency as well as within the same recording, which is required for the events to be discriminated. For wavelets with centre frequencies above 92 Hz, time resolution is between 25 ms and 10 ms. In signals of mixed frequencies and when comparing peaks recorded in different trials, time resolution is much shorter and mainly limited by the sampling frequency. Centre frequencies higher than 395 Hz were omitted because of high frequency noise. EMG power at each time point was calculated by summing the power extracted by the wavelets with centre frequencies of 92 Hz to 395 Hz. The EMG power over a time period encompassing 200 ms before and 200 ms after heel strike was used for the analysis. The average EMG power of the triplicate electrodes was called a waveform. Therefore, heel strike was at time 0 within the waveform. Waveforms were normalised by dividing them by the sum across the waveform. The waveforms indicate the fine structure across time of the step-specific strategy of muscle activation. Each individual waveform stands for the average waveform of all steps for a given subject. The group waveform was computed by averaging the individual waveforms of all subjects.

Timing Analysis

The time occurrence of all peaks (peak locations) with an intensity level higher than 1% of the maximum peak value was extracted from all waveforms and from the group waveforms in order to avoid the detection of small oscillations around zero [31]. Raster plots of the peak locations were generated with a time resolution of 6 ms, showing the peak locations (x-axis) for the different steps or muscles (y-axis). A colour mapping was separately applied on the dots in the multi-step raster plots in the pre and the post heel strike period. The colours’ order was equal for all raster plots. It started at heel strike with a backward and a forward mapping in the pre as well in the post heel strike period, like, for example, all first detected peaks after heel strike are mapped with the colour pink. The difference in time between two adjacent intensity peaks was calculated for all waveforms. A histogram of these inter-pulse intervals was generated, representing their probability distribution. A Lilliefors test was used to asses, if the inter-pulse intervals were normally distributed. The significance level was set at $p < 0.05$.

All computations were made in custom software implemented in Matlab (MathWorks, Version R2010b, Natick, MA, USA).

RESULTS

The average walking speed of 10 healthy females was 1.22 ± 0.06 m/s (range 1.14 – 1.29 m/s). In general, the waveforms indicate the fine structure across time and reveal a step-specific strategy of muscle activation, while the individual waveforms describe the subject-specific muscle activation strategy while walking.

Group Analysis

The comparison of the group waveforms – the averages of the individual waveforms – is shown in Figure 2 and illustrates the basic activation patterns at the slightly different positions on the muscle recorded by the triplicate electrode pairs. The similarity between the waveforms of the triplicate electrode pairs was visually checked for each step and subject. This visual inspection showed that only the waveforms of the three BF electrodes had a large variation in shape with the position of the electrodes. This meant that the EMG signal yielded a non-reliable activation pattern for BF. Either the patterns of different muscle compartments or of multiple muscles were reflected. The other muscles showed a consistent activation pattern with only slight but detectable spatial differences. So only the activation pattern of the QF muscles and ST were used and commented in the detailed analysis. Yet, the locations of the peaks weren't shifted between recordings from the medial or lateral side, as shown in the raster plot of Figure 3. And because of this, a muscle was activated at the same time across the medial-lateral region. For that reason, the detailed analysis will therefore be limited to the data recorded from the original electrode position.

The group waveforms of the QF muscles revealed three ranges containing distinct peaks or features. The pre heel strike range lasted from -90 ms to heel strike and contained a distinct peak at -50 ms for RF. For QF, the first post heel strike range was characterised by a peak at +35 ms and was followed by a second post heel strike range, characterised by a peak at +75 ms, which rapidly decayed and ended +150 ms after heel strike (Fig. 2A, C and E).

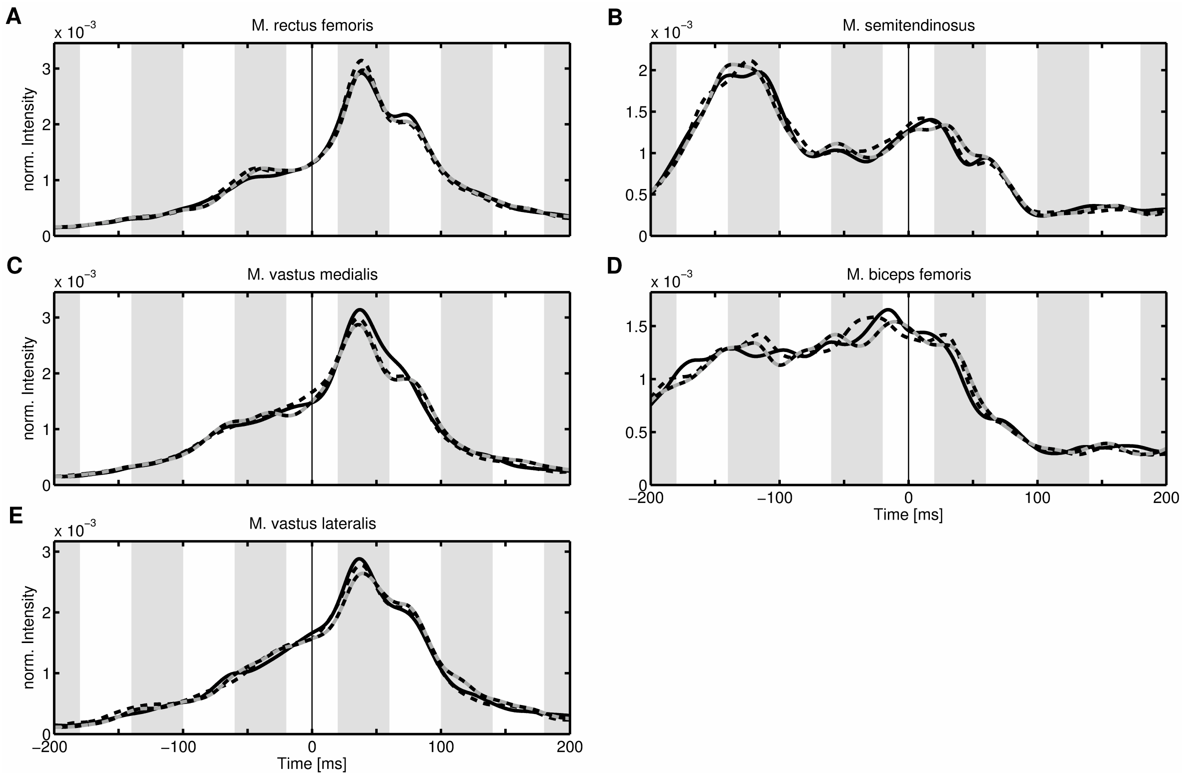

FIGURE 2. Line graphs of the group waveforms of (A) M. rectus femoris, (B) M. semitendinosus, (C) M. vastus medialis, (D) M. biceps femoris and (E) M. vastus lateralis are illustrated for the lateral (black solid line), original (black dashed line) and medial (grey-black dashed line) electrode position. Time 0 indicates heel strike (vertical black line).

The group waveforms of ST (BF could not be included) showed its main activation in a peak occurring 125 ms before heel strike (Fig. 2B). The next peak occurred in the pre heel strike range of the QF muscles, thus reflecting a co-contraction.

The time between the peaks are illustrated in a multi-muscle raster plot (Fig. 3), which reflects the interplay of muscles, based on the group waveforms and characterises the basic activation strategies of the group while walking. A time delay of 85 ms (2 x 42.5 ms) between the pre heel strike peak and the first post heel strike peak of RF as well as of 40 ms between the first and second post heel strike peaks of RF, VM, VL and ST were found. On average, the peaks occurred in a raster of about 40 ms.

To obtain such distinct peaks as shown in Figure 3, the individual waveforms have to be well aligned. The details of the alignment will be revealed by the between subject analysis.

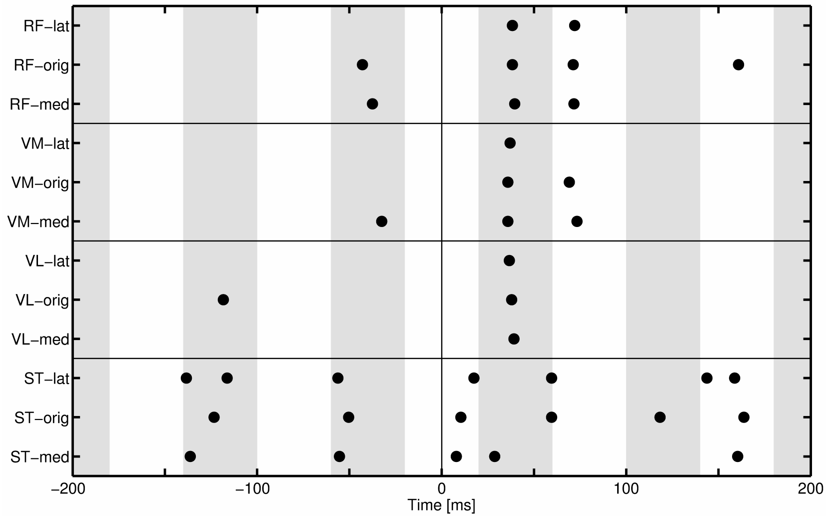

FIGURE 3. Multi-muscle raster plot with peak locations (x-axis) detected in the group waveforms of the M. rectus femoris (RF), M. vastus medialis (VM), M. vastus lateralis (VL) and M. semitendinosus (ST) (y-axis, top down) are illustrated for the lateral (lat), original (orig) and medial (med) electrode position. Time 0 indicates heel strike (vertical black line).

Between Subject Analysis

The individual waveforms (the average of the waveforms) of the subjects that describe the subject-specific average muscle activation are shown for the QF muscles and ST in Figure. 4. The individual waveforms were subject-specific; yet, similarities between subjects were apparent in the peak locations and not in the shape of the waveforms. The peaks of the QF muscles, which occurred during the pre heel strike range (-90 ms to heel strike) varied in amplitude and position between the subjects (Fig. 4A-C).

This explained that during the pre heel strike period, the timing of the peaks weren't tightly controlled. In contrast, the first post heel peak at +35 ms was present in all subjects, however with varying intensity. The peak in the second post heel strike region was also located close to +75 ms, but wasn't present in all subjects. Summing up, the QF muscle activation in the post heel strike period was well synchronised to heel strike and was dominated by peaks occurring in the 40 ms raster that was already observed in the group waveforms.

The ST, in contrast to the QF muscles, didn't generally show a systematic alignment of peaks. Yet, some subjects activated the muscle with a peak at +35 ms and +75 ms, hence, in synchrony with the QF muscles, but this was the exception. In summary, each of the ten subjects had their individual activation patterns with distinct peaks at mostly the same specific time points.

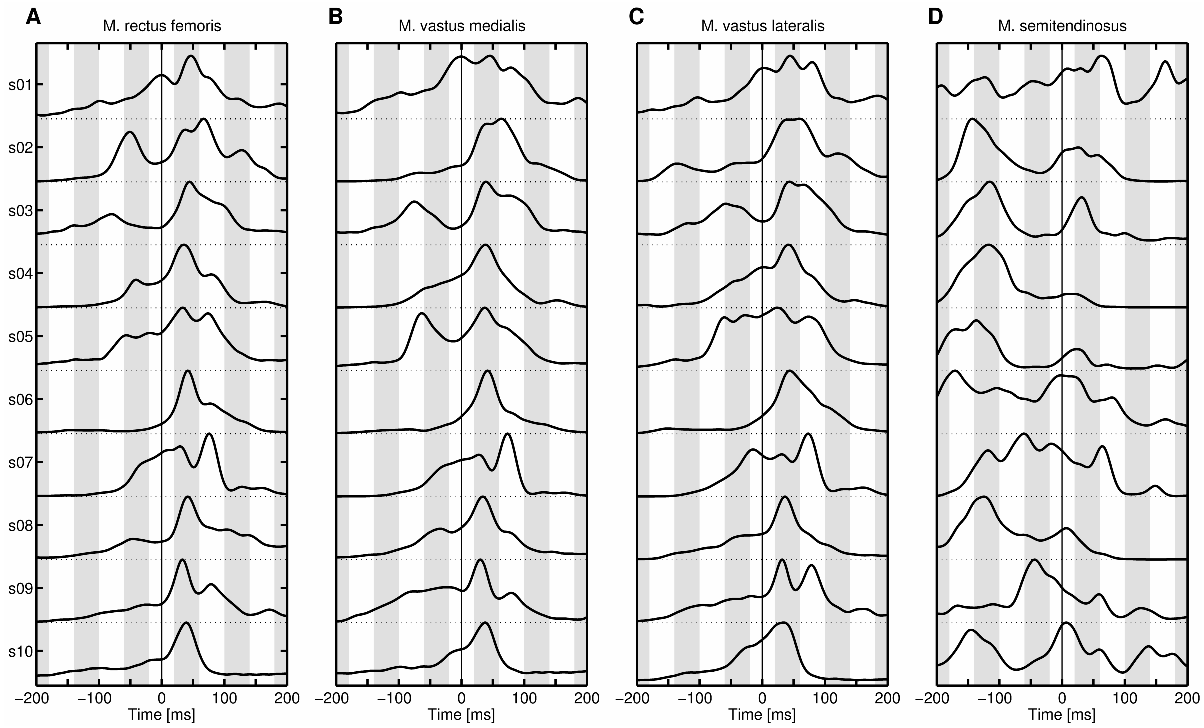

FIGURE 4. Line graphs of the individual waveforms of (A) M. rectus femoris, (B) M. vastus medialis, (C) M. vastus lateralis and (D) M. semitendinosus (D) obtained from subjects #1 to #10 (s01 to s10; top down). Each line represents the average across all waveforms. Time 0 indicates heel strike (vertical black line).

Within-subject Analysis

Only the first two post heel strike peaks of the QF muscles appeared consistently in most individual waveforms. The within-subject analysis of any repetitive occurrences of peaks was therefore limited to the QF muscles. The waveforms of the steps of two extreme subjects (subjects #6 and #8) – one with high and one with low repeatability between the waveforms – are shown for RF, as an example, together with the multi-step raster plots in Figure 5. The waveforms reveal the step-specific strategy of muscle activation within a subject. The raster plots show the step-to-step temporal distribution of the peaks across all steps. The same-coloured dots are mostly arranged in a band with loose dots (outliers) of other colours. Nevertheless, a distinct separation, based on a raster plot, that would have allowed a statistical assessment of the separation of the bands failed because the jitter was too large. The within-subject variability could therefore only be reported by showing the waveforms of individual subjects and qualitatively relating them to the raster plot.

Subject #6 showed consistent repeats of muscle activation for each step, especially for the main peak at +35 ms (*SD* = 2.3 ms) that yielded a narrower bandwidth with one outlier in the raster plot (pink dots in Fig. 5E). The second peak occurred with a jitter around +75 ms and occasionally, the muscle was activated by the third or higher order peak. The raster plot discriminated the first two post heel strike peaks, whetheas the other peaks, whether pre or post heel strike, didn't visibly fall onto a distinct raster. A similar phenomenon was found in a second subject, subject #9.

Subject #8 showed less consistency of the waveforms. Some well-controlled precise timing was apparent by a nearly vertical alignment of pink dots, which consequently led to a relatively narrow band with loose outliers (Fig. 5F). The remaining bands consist of more scattered dots and so with broader bandwidths. Thus, only the individual waveform (Fig. 5A-B) together with the raster plot (Fig. 5E-F) indicated that the pulses had some systematic occurrences. For example, the individual waveform of subject #8 illustrated a preferred activation of the last band before heel strike, which corresponded to the yellow dots in the raster plot.

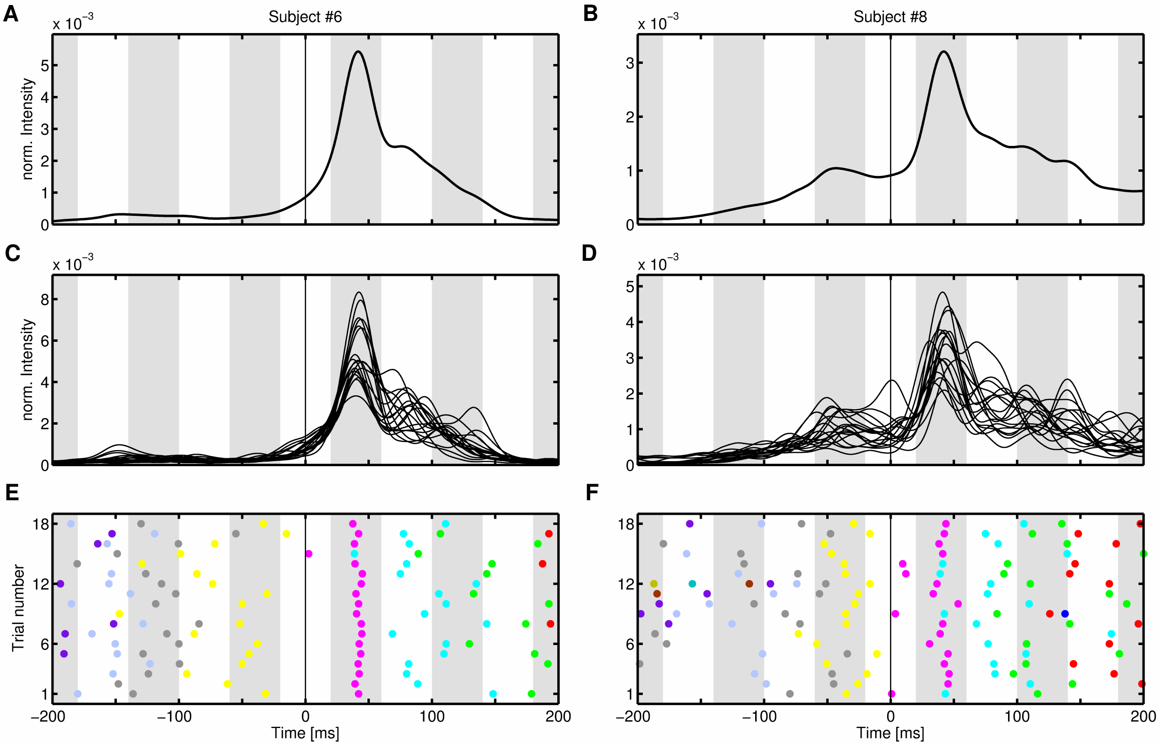

FIGURE 5. Line graphs of the individual waveforms (A-B) and the waveforms for all steps (C-D) for M. rectus femoris are shown together the with multi-step raster plots with peak locations (x-axis) detected in 18 waveforms (y-axis) (E-F) for subjects #6 (left) and #8 (right), respectively. Time 0 indicates heel strike (vertical black line).

Last but not least, the analysis of all 20'032 inter-pulse intervals revealed a standard right-skewed gamma-distribution with the scale parameter $\theta = 11.22$, the shape parameter $k = 4.57$ and the maximum value at 39.7 ms (Fig. 6). The skewness value was 1.92 and was significantly different from normal distribution ($p < 10^{-3}$) for the inter-pulse intervals.

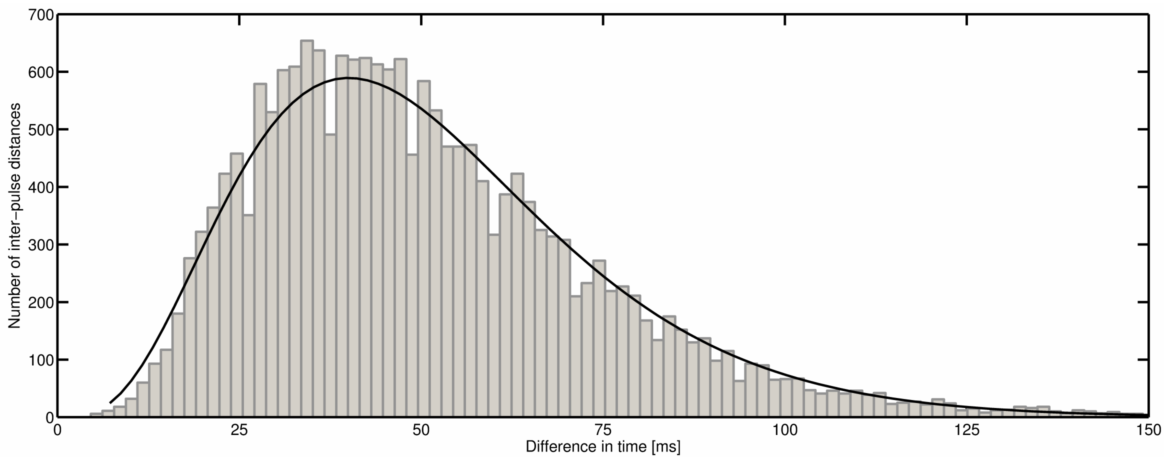

FIGURE 6. Histogram of 20'032 inter-pulse intervals (grey area) of all 10 subjects across all waveforms (without averaging across the triplicate electrode pairs) is illustrated. The black line is the gamma distribution fit to the data.

In summary, the within-subject analysis showed that, even though, there was a lot of jitter in the locations of the peaks, the individual waveform revealed a structure, showing distinct peaks. The activation during each step distributed the motor unit action potentials in a step specific way but on average, on a kind of predefined, but not utterly precise raster.

DISCUSSION

The basic activation pattern of RF, VM and VL in the group analysis indicated a high intra- and inter-muscular coordination (Fig. 2A, C and E) for the entire QF muscle. The EMG signal combined with the wavelet-based analysis of this signal was sufficiently sensitive to detect a synchronisation of the activation of thigh muscles while walking. The neuromuscular control uses a raster-like timing frame for the synchronisation of muscle activity during gait. The raster-like timing frame, on average about 40 ms, seems to control the pacing of the neuromuscular activity. This raster isn't limited on one pulse, but on the whole sequence of -200 ms to +200 ms and is shown in the figures (Figs. 3-5) by the underling grey shaded areas. The pacing frequency of different subjects were spread across a small range, hence, the averaging of the individual waveforms did resolve the pacing properties of the neuromuscular control. Yet, in contrast to maximally activated muscles [4, 34, 35] and to running [31] where the neuromuscular rhythms are precisely controlled, walking is a movement that has more degrees of freedom and therefore doesn't need a tight control of muscle activity. This movement laxitiy is reflected in the jitter of the timing and amplitudes of the muscle activation during individual steps. Nevertheless on average, this activity seems to be controlled at 40 ms intervals. The study indicates that there is a balance between a strictly paced neuromuscular control and a more random recruitment of motor units.

The raster of 40 ms is both subject and muscle independent. Our result agrees with earlier findings showing rhythmicity in skeletal muscles [4, 31, 32, 34, 35] and support the idea of previous studies that temporal patterns and rhythms are represented by the central drive to muscles [3, 4, 29-32, 34]. It is conspicuous that the raster is synchronised to the time of heel strike. It seems that the neuromuscular system has the ability of adapting to an external trigger, in this case the heel strikes [1, 2, 31, 36], whereas ST and the QF muscles have different controlling strategies. The ST is triggered in the pre heel strike period and the QF muscles, which requires knowledge from previous heel strikes to estimate the time of the next ground contact. The jitter of the pacing seen in the raster plot reflects the muscular coordination at heel strike. It seems that subjects with a more pronounced inhomogeneity of peaks around heel strike required a lower neuromuscular control anticipation of the next heel strike. The control works like a pre-programmed adaptive feedback activation.

The precise peak locations in this study verify the theoretical predictions of Hof [15] obtained by a simulation study. Hof [15] affirmed that equal gait movements could be generated by identically timed muscle activation, only by changing the activation amplitudes. In our view, subjects with a high precision of waveforms seem to have the ability to better adapt the muscular system on exterior influences by changing their pre-programmed activation. Based on the subject-to-subject variation in shape but not in peak locations, the variations could originate from varied muscular recruitments, physiological and morphological properties of the muscle. Particularly, features changing the muscle morphology (e.g. size, fibre-type proportion [39]) as well as the interplay between and within muscles caused by various training regimes [16, 41] can change the neuromuscular control reflected by the waveforms. But also, between-subject variability, it most likely reflects that different activation patterns are used to generate the same movement [17]. To stabilise a preferred movement pattern and react to varying forces, the neuromuscular control has to adapt [19].

The observed EMG intensities reflect the specific timing around heel strike of the activation of the major thigh muscles while walking. This timing is important to coordinate co-contraction of the QF muscles and its antagonist ST (antagonist-agonist interplay) and to achieve preparatory knee positioning before initial contact. Precisely timed co-contraction is needed to regulate stiffness of the muscular system that is required to tolerate and absorb high impact forces.

The precise timing is also important for regulating the synergistic function of the QF muscles stabilising the knee joint at the time around heel strike. A balanced activation of VM and VL is known to prevent a patellar maltracking [6, 21, 22], reduce the stress on the anterior cruciate ligament [14] in addition to supporting a dynamic knee joint stability. A more holistic functional consideration was used by Clark et al. [5], Gizzi et al. [9] and Monaco et al. [23]. They refer to muscle synergies, also called muscle modules. These articles conclude that there may be a limited number of about four driving sources controlling between 8 and 32 muscles. In these cases, the activation timing profile were resolved with a time resolution estimated to be larger than 100 ms and so represent a different aspect of muscle activation than the one presented here. The time resolution was so large that the activation timing profiles don'tt reflect the fine structure of the 40 ms raster observed in the present study. It might well be that the observed activation timing profiles shown by Clark et al. [5] might show a superimposed rhythm of 40 ms, if resolved with more details. It would be interesting to see, if the activation timing profiles could be seen as structures paced at about 25 Hz, a frequency corresponding to the beta waves of the brain. In that case one could speculate that the modules represent a means of weighing the underlying 25 Hz pacing before sending the commands to the muscles.

The study shows that the wavelet-based analysis of the EMG signal was sufficiently sensitive to detect a synchronisation of the activation of thigh muscles while walking. The peak muscle activation predominantly occurred at times that fit a raster-like frame of about 40 ms, yet with variable amplitudes. Albeit the jitter of the signal, the results resolved the temporal dependency of intensity peaks within muscles surrounding the knee joint and provided an insight into neural control of locomotion. The methodology to assess the stabilising muscle activation pattern can provide a way to discriminate subjects with normal gait pattern from those with a deteriorated neuromuscular control strategy. In future, we will apply further analysis methods, like, for example, principal component analysis to resolve different activation strategies between the subjects.

CONFLICT OF INTEREST

The authors report no potential conflict of interest or the appearance a conflict of interest with regard to the study presented in this paper.

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Chapter 4

Dominant Neuromuscular Control Strategies used by Females While Walking

A movement emerges from the interrelationship between the task, the individual, and the constraints of the environment. Thus, multiple systems have to cooperate. The electromyographic (EMG) signal is a common measure to reflect the neuromuscular control strategies during dynamic tasks. The purpose of this study was to identify neuromuscular activation strategies, which are used by different subjects while walking. The EMG power, extracted by the wavelet transform (92–395 Hz), over a time period encompassing 200 ms before and after heel strike was analysed by using a principal component analysis. The study showed that the neuromuscular control of the general activation pattern is modulated by two well-defined strategies which are recruited in a subject-specific way. These two detectable strategies manipulate the amplitude of the peaks and valleys of the EMG waveforms, which are closely related to a raster of about 40 ms. It seems that the time frame around heel strike allows individuals certain flexibility in how they balance their pre and post heel strike muscle activation. The study shows that quantifying neuromuscular activation patterns provide an insight into the neuromuscular behaviour within as well as between muscles and its effect on the motor output is possible through using the principal component analysis approach on wavelet-based analysis of EMG signals.

Key words: *Gait, EMG, Wavelet analysis, principal component analysis, neuromuscular control strategies.*

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ABBREVIATIONS

BF, M. biceps femoris; *EMG*, electromyography; *HAM*, hamstring muscle group; *MRW*, Mean Reconstructed Waveform; *PC*, principal component; *PCA*, principal component analysis; *QF*, Mm. quadriceps femoris; *RF*, M. rectus femoris; *SERW*, Standard Error of the Reconstructed Waveforms; *ST*, M. semitendinosus; *VL*, M. vastus lateralis; *VM*, M. vastus medialis.

INTRODUCTION

In daily locomotion, a uniform and stable movement pattern increases human mobility, independence and quality of life. Movements, like walking, require the coordination and control of multiple muscles in a specific sequence of events occurring at precise time points [38]. Walking is possible, because of the interplay of the nervous and the musculoskeletal system. The many degrees of freedoms of the musculoskeletal system provide great flexibility, but make the control strategy extremely complex. Although walking is a constrained movement, there is variation in the muscle recruitment patterns [10, 41] as certain common features, like rhythm within the electromyographic (EMG) signal and/or triggering to heel strike were present in many muscles across individuals [13, 35]. So muscles share certain activity profiles [4] and/or activity behaviours [3, 16].

It was shown in a previous study that EMG signals recorded from the thigh muscles while walking revealed peaks of the EMG power at a rhythm of about 40 ms, which were synchronised to the time of heel strike [13]. Similar rhythms have been found in the *M. abductor pollicis brevis* during isometric contractions [37] and in the M. *gastrocnemius medialis* while running [32]. These rhythms can reflect the pacing known as Piper rhythm and supposedly mirror a corticomuscular interaction [6, 30]. The neuromuscular control seemed to be paced with this rhythm, varying the amplitude at the times, where the maxima of the EMG power occurred [13].

Especially at heel strike, where the human locomotor system is affected by irregular impact forces, controlled muscle activation strategies, rapid central processing, plus accurate motor control of strong muscles are essential for counteracting the destabilising forces to keep the knee joint stable [26]. Therefore, a movement depends on the interrelationship between the task, the individual, as well as on the constraints of the environment. Thus, multiple systems have to cooperate. Previous muscle coordination studies have shown that many movements in humans are neural predetermined [34] and can be described by the weighted combinations of a number of muscle activation patterns (e.g. [1, 8, 10, 18, 23, 33]).

The study's purpose was to identify neuromusuclar activation strategies of muscles surrounding the knee joint extracted from the measured EMG signal, used by different subjects while walking at their self-selected speed. The result should explain how humans use strategies for muscle tuning [26], before heel strike or for post heel strike reaction to the impact. To extract these strategies, a principal component analysis (PCA) was applied. The PCA approach on EMG signals has previously allowed extracting information about the neuromuscular processes [4] and the real physiological information about the nature of the movement's coordination [1]. Because of that, this study should answer the questions, how individuals prepare the thigh muscles, and specifically those controlling the knee actively, for absorbing the impact at heel strike and if dominant activation strategies exists between individuals; hence, the study should yield a deeper insight about the neuromuscular control mechanism in the motor output.

MATERIALS AND METHODS

Subjects

The study group consisted of ten healthy female volunteers [age: 48 ± 7 years, body mass: 61.1 ± 4.9 kg, height: 1.64 ± 0.05 m] with no history of lower extremity surgery, no osteoarthritis of the hip or knee joint, no neurological, or musculoskeletal impairments. They were informed about the measurement procedure and signed an informed consent form. The local Ethics Committee approved the study design.

Study Design

The study protocol consisted of an instrumented three-dimensional gait analysis with synchronous measurement of the thigh muscle activity during normal level walking. The lower body kinematics were collected by using a six-camera, 240 Hz motion capture system (Vicon MX13+, Oxford, UK) and the Helen Hays marker model [20]. The subjects walked barefoot at a comfortable, self-selected walking speed along a 10 m walkway in the laboratory. In the end, a total of 180 steps from the left leg – 18 steps per subject – were analysed. The time of heel strike was determined from the position of the heel marker.

Data Recording

Surface EMG signals from the quadriceps femoris (QF) muscles: *M. rectus femoris* (RF), *M.vastus medialis* (VM), and *M.vastus lateralis* (VL), plus the hamstring (HAM) muscles: *M. semitendinosus* (ST) and *M. biceps femoris* (BF) from the left thigh were detected with bipolar Ag/AgCl surface electrodes (diameter: 10 mm, inter-electrode distance: 22 mm, Noraxon U.S.A Inc., Scottsdale, AZ, USA). The ground electrode was positioned over the tibial tuberosity. According to the SENIAM-recommendations [12], the skin preparation and the electrode placement were done. The electrodes were connected to single differential amplifiers (band path of 10-700 Hz, Biovision, Wehrheim, Germany). The EMG data was sampled at 2'400 Hz without further processing. Elastic net bandages (Elastofix, Type B, BSN medical GmbH & Co. KG, Hamburg, Germany) were pulled over the thigh to keep cables and electrodes in place.

EMG Signal Processing

Wavelet Transform

The signal analysis was performed using a time-frequency analysis consisting of 13 non-linearly scaled wavelets [36] yielding time and frequency distribution of the power of the EMG signal. Moreover, the information about the muscle activity is contained in both, low and high frequency components of the EMG signal. But to extract the rhythmicity of the power, it was important to use a frequency range, where the time resolution of the wavelet transform was short enough to resolve the rhythm. Therefore, centre frequencies lower than 92 Hz weren't considered. High frequency noise was eliminated by using only the power of the wavelets with centre frequencies up to 395 Hz. Consequently, the EMG power at each time frame was calculated by summing the power extracted by the wavelets with centre frequencies of 92 to 395 Hz. The EMG power used for the analysis was cut into periods, ranging of 200 ms before to 200 ms after heel strike and is referred to as a waveform in the following. Heel strike was at time 0 within the waveform. Waveforms were normalised by dividing them by the sum across the waveform; they were thus waveforms representing a power of 1. A waveform indicates the fine structure across time of the step-specific strategy of muscle activation. For each subject and muscle an individual waveform was computed, representing the average waveform of all steps. The group waveform of each muscle was computed by averaging the individual waveforms of all subjects.

Principal Component Analysis

Principal component analysis [19] has been widely used in the fields of biomechanics and was often applied in the past for the analysis of EMG signals [4, 9, 22, 27, 42]. The PCA requires that the waveforms are arranged in a matrix. For each muscle indexed with m, a matrix X_m was formed, containing 180 waveforms – 18 waveforms per subject – aligned in rows where the average of the 180 waveforms – the group waveform – was subtracted. Because of this, five separate PCAs, one for each muscle, were separately applied on matrix X_m. The principal component vectors (PC-vectors) were the eigenvectors of the covariance matrix of X_m. They span the vector space of the waveforms and are orthogonal. PC-scores were obtained by projecting the waveforms onto the PC-vectors. PC-vectors were numbered and ordered descending, according to their eigenvalues. The eigenvalues represent the variance of the PC-scores. The sum of all eigenvalues represents 100% of the variance.

For each subject and muscle, the average PC-scores of each PC of the 18 waveforms were computed. Multiplying the average PC-scores with the corresponding PC-vectors and adding the sum of the results to the group waveform obtained a reconstructed average individual waveform. Accordingly, each reconstructed average individual waveform is a linear combination of the PC-vectors weighted by the appropriate average PC-scores plus the group waveform. The PC_1- and PC_2-vector represent the main cause of variability and thus contain an important part of the information about the neuromuscular control and coordination of the muscles.

The reconstructed waveforms were computed for each subject and muscle by multiplying the PC-scores with the corresponding PC-vectors of the first two PC-scores for the QF muscles and the first three PC-scores for the HAM muscles. For each time point, subject and muscle, the individual Mean Reconstructed Waveform (MRW) and the Standard Error (SERW) of the reconstructed waveforms were calculated. The SERW reveals fluctuations related to higher-order PCs. The difference between the individual waveform and the reconstructed average individual waveform is illustrated as the grey shaded area in Figure 1. The grey shaded area represents two SERWs of MRW added to the individual waveform. The higher-order PC-vectors contain the variability of the EMG signal, which isn't included in the reconstructed average individual waveform.

Relationship Between PC-scores and Statistical Analysis

The Pearson correlation coefficient, r, was used to determine the relation (i) between the PC_1- and PC_2-scores in all five muscles, and (ii) between muscle pairs (e.g. RF versus VM (RF-VM), and so on) for the first two PC-scores separately. A significance level of $p<0.05$ was chosen.

Every analysis and statistical testing was performed in Matlab (MathWorks, Version R2010b, Natick, MA, USA).

RESULTS

General Aspects of the Muscle Activation While Walking

The individual waveforms of the QF and HAM muscles of 10 subjects are shown in Figure 1 together with the reconstructed average individual waveforms sorted ascending by the PC_1-scores of RF. Each black line describes the muscular timing for any given subject with respect to the basic activation strategy as indicated by the first two or else the first three PC-vectors. The divergence of the reconstructed average individual waveform to the waveforms – as illustrated by the grey shaded area in Figure 1 – is a result of the fluctuations described by the PC-vectors with higher-order. The grey shaded area was mostly wider for the HAM muscles than for the QF muscles. Therefore, less signal variability could be explained by the first three PCs.

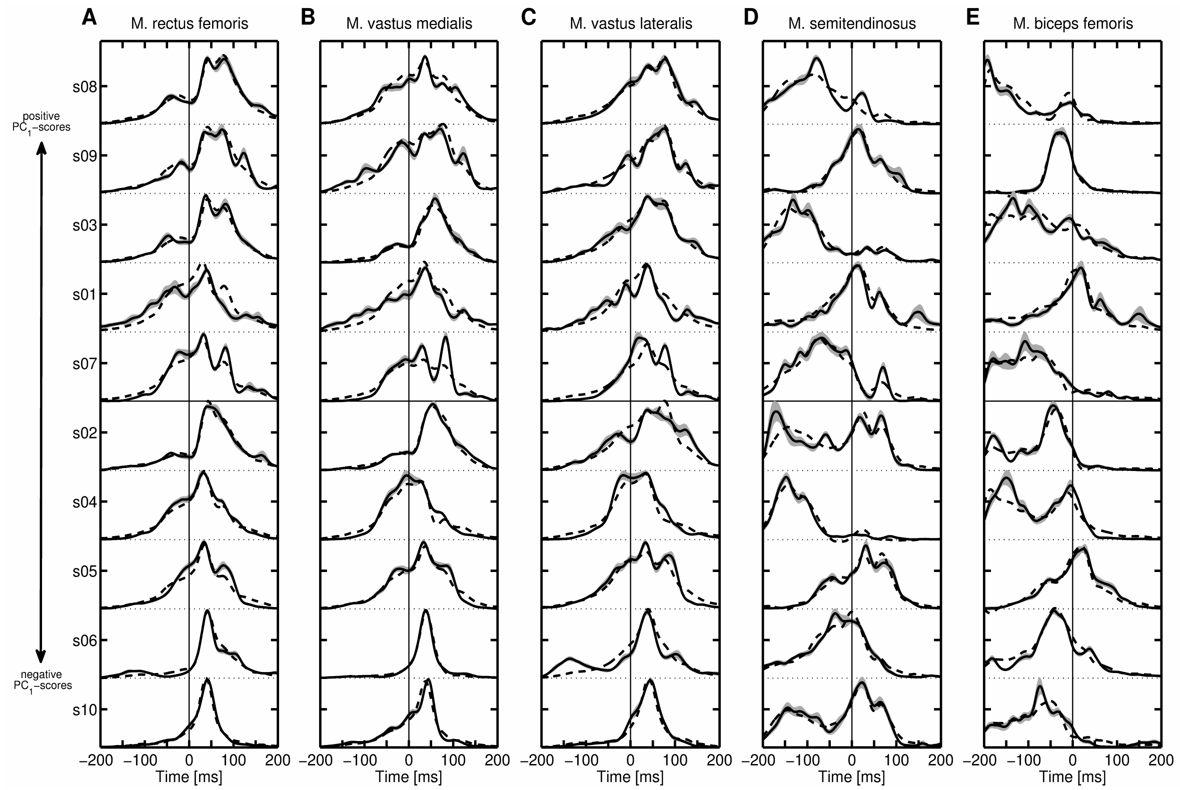

FIGURE 1. Line graphs representing the individual waveforms (black solid lines) and the reconstructed average individual waveforms containing (A-C) the first two and (D-E) the first three PCs (black dashed lines) of (A) M. rectus femoris, (B) M. vastus medialis, (C) M. vastus lateralis, (D) M. semitendinosus and (E) M. biceps femoris for the 10 subjects (s01 to s10; sorted ascending by the PC_1-scores of M. rectus femoris (top down)). For a better visualisation, the individual graphs were scaled by their maximal ranges. Horizontal solid black lines indicate the transfer from positive to negative PC_1-scores. Time 0 indicates the heel strike (vertical black line). The grey shaded area represents two SERWs of MRW added to the individual waveform.

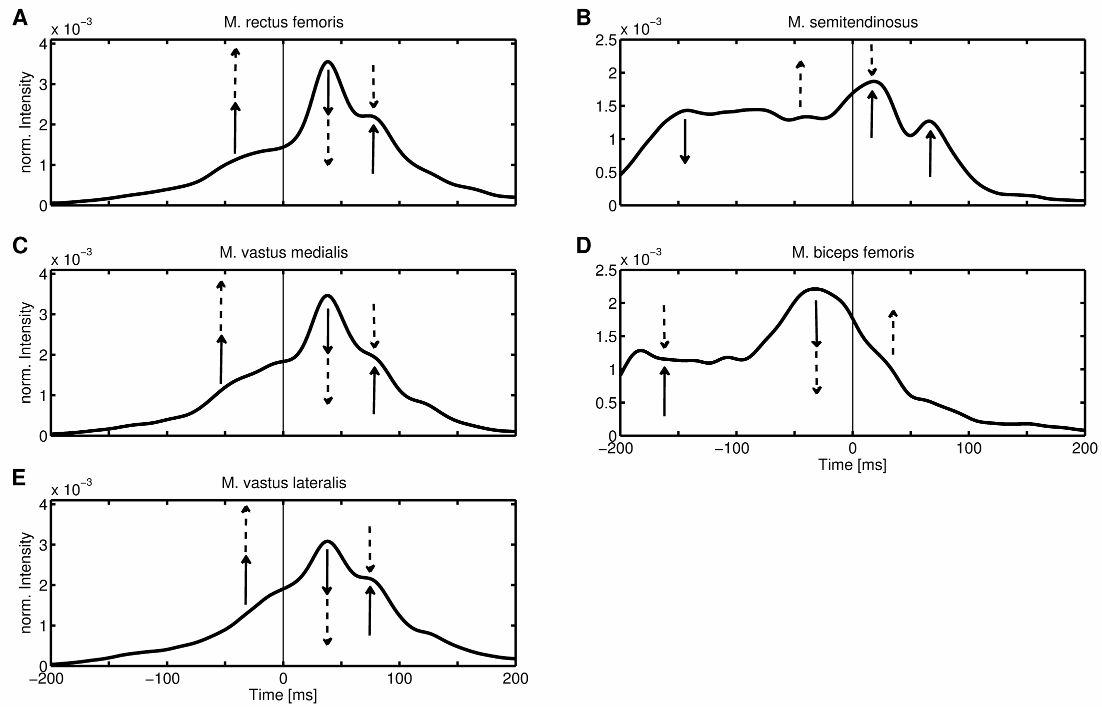

FIGURE 2. Line graphs representing the group waveforms of (A) M. rectus femoris, (B) M. semitendinosus, (C) M. vastus medialis, (D) M. biceps femoris and (E) M. vastus lateralis. The arrows display the effect of the PC_1- (solid arrows) and PC_2-vector (dashed arrows) on the group waveforms. Time 0 indicates heel strike (vertical line).

The group waveforms – the averages of the individual waveforms – are shown in Figure 2 and demonstrate the basic group activation patterns around the time period of 200 ms before and after heel strike. The universal effect of the PC-vectors can be seen by observing the shape of the PC_1- and PC_2-vectors in Figure 3. The reconstructed average individual waveforms of the PC_1- and PC_2-vector, obtained from the various PC-scores and sorted ascending to these scores, are shown in Figures 4 and 5. They confirm that each individual modifies the group waveform by adding a subject-specific amount of the control strategy indicated by the PC_1- and PC_2-scores.

There were no detectable correlations observed between the PC_1- and PC_2-scores in all five muscles. The *r* values ranged from $-1.88*10^{-16}$ to $2.59*10^{-17}$ and showed that these two features were independent, uncorrelated variables.

Waveforms of the Quadriceps Femoris Muscle Group

The PC_1-vectors of RF, VM and VL – obtained from 180 waveforms – explained 32.5%, 40.2% and 30.0% of the total variance, respectively, and had a shape that was similar to one another (Fig. 3A, C and E, solid lines). The variability of the EMG power of the QF muscles stands for an intensity exchange between the peaks occurring during the pre and the post heel strike period, spatially centred at -35 ms, +35 ms and +75 ms, as illustrated in Figure 2A, C and E with solid arrows. The PC_1-vectors with its negative and positive peaks positioned at +35 ms and +75 ms, respectively, supported the fact that the peak at +35 ms was visible in the individual waveforms of all subjects and the peak at +75 ms, the one with the lower absolute value, was different strongly expressed in the individual waveforms of all subjects (Fig. 1A-C).

The reconstructed individual waveforms matching to positive and negative PC_1-scores confirmed these findings (Fig. 4A-C): The PC_1-vector illustrates a transfer from higher pre heel strike muscle activation with a pronounced multimodal activation pattern in the early post heel strike period (positive PC_1-scores) to a reduced pre activation with a pronounced unimodal post activation (negative PC_1-scores).

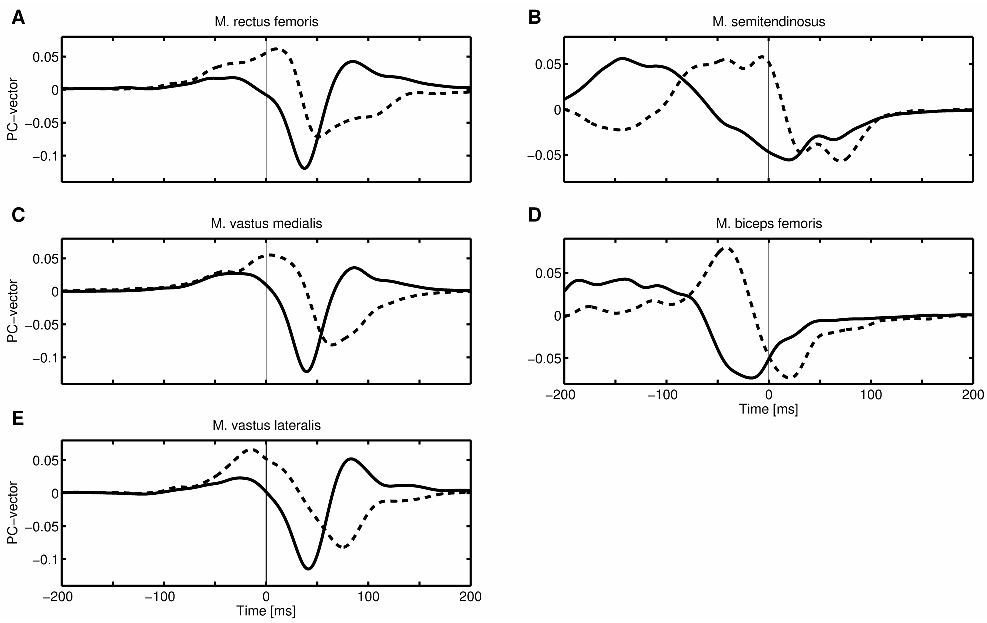

FIGURE 3. Line graphs representing the PC_1- (solid lines) and the PC_2-vectors (dashed lines) of (A) M. rectus femoris, (B) M. semitendinosus, (C) M. vastus medialis, (D) M. biceps femoris and (E) M. vastus lateralis extracted by the 180 waveforms. Time 0 indicates heel strike (vertical line).

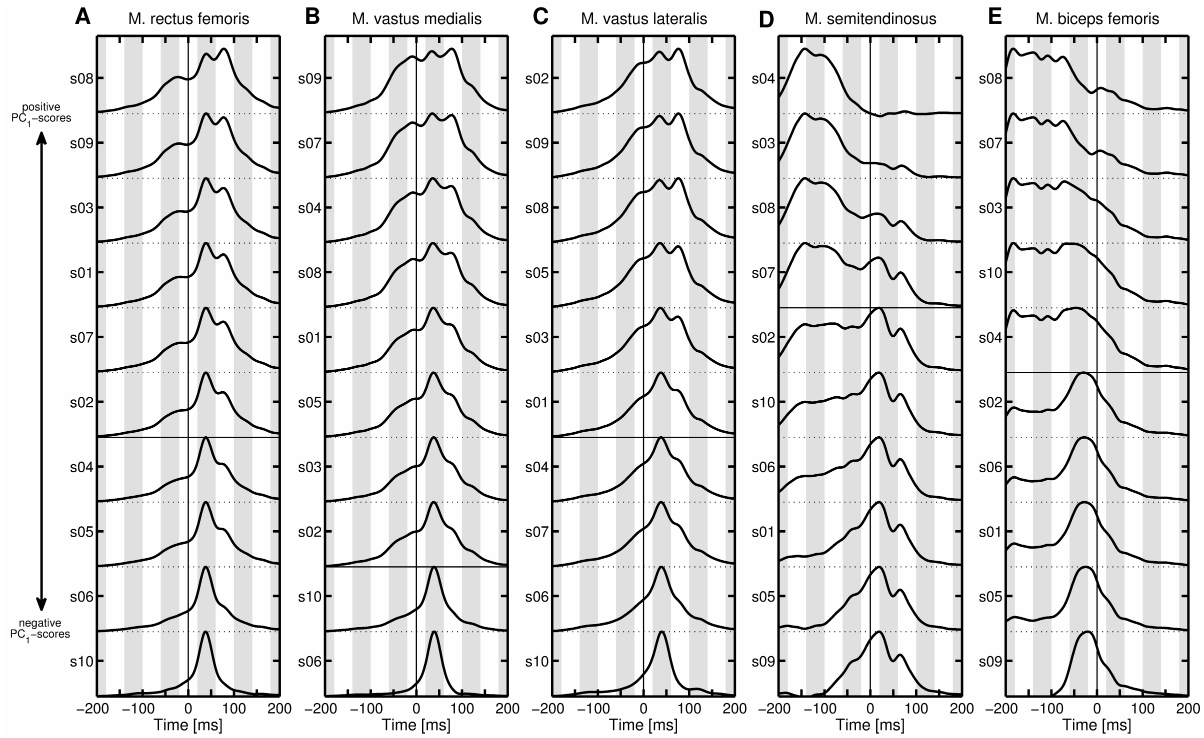

FIGURE 4. Line graphs of the reconstructed average individual waveforms corresponding to the averaged PC_1-scores are sorted ascending from positive to negative scores (top down) for (A) M. rectus femoris, (B) M. vastus medialis (C) M. vastus lateralis, (D) M. semitendinosus and (E) M. biceps femoris for subject #1 to subject #10 (s01 to s10). These graphs assist in the interpretation of the patterns associated with the PC_1-scores. For a better visualisation, the individual waveforms are scaled to their maximal values. Horizontal solid black lines indicate the transfer from positive to negative PC_1-scores. Time 0 indicates heel strike (vertical black line). The grey pattern in the background stands for the average pacing frequency of the EMG power described in our previous paper [13].

The explained variability of the PC_2-vectors of the RF, VM, and VL was 22.5%, 20.0%, and 16.9% of the total variation (Fig. 3A, C and E, dashed lines). They were mostly associated with the intensity swap between the peaks located at +35 ms and +60 ms (for RF and VM) or between the peaks located at -20 ms and +60 ms (for VL) shown in Figure 2A-C with dashed arrows. The PC_2-vectors and the group waveforms of RF and VM had similar shapes, and therefore had an equal effect on the reconstructed individual waveforms shown in Figure 5A and C. These two muscles, subjects showing positive PC_2-scores had increased muscle activation shortly before heel strike plus a strong bimodal for RF or unimodal for VM activation patterns in the post heel strike period. On the contrary, subjects with negative PC_2-scores showed both reduced muscle activation before heel strike and strong increasing muscle activation shortly after heel strike. For the VL, positive PC_2-scores led to a multimodal activation pattern in the period from -25 ms to +50 ms and negative PC_2-scores showed increasing muscle activation from -100 ms to +45 ms with a bimodal activation pattern in the post heel strike period.

The results of QF illustrated that differences in shape (relative amplitude) but not in the peak location exist between the subjects. The PC_1-vectors of the QF muscles showed that the intensity swap occurred between the pre and the post heel strike period as well as within the post heel strike period, while the PC_2-vectors revealed the intensity exchange between the two post heel strike peaks with an additional effect on the slope shortly before heel strike.

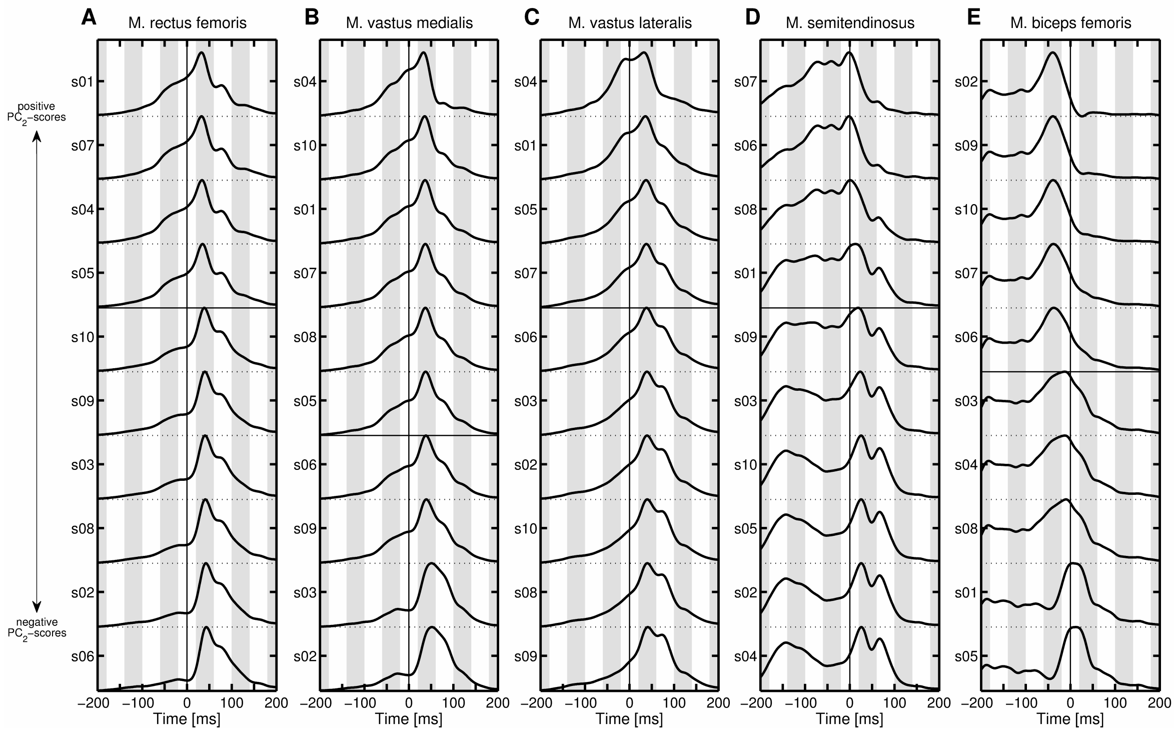

FIGURE 5. Line graphs of the reconstructed individual waveforms corresponding to the averaged PC_2-score are sorted ascending from positive to negative scores (top down) (A) M. rectus femoris, (B) M. vastus medialis, (C) M. vastus lateralis, (D) M. semitendinosus and (E) M. biceps femoris for subject #1 to subject #10 (s01 to s10). These graphs assist in the interpretation of the patterns associated with the PC_2-scores. For a better visualisation, the individual waveforms are scaled to their maximal values. Horizontal solid black lines point towards the transfer from positive to negative PC_2-scores. Time 0 indicates heel strike (vertical black line). The grey pattern in the background represents the average pacing frequency of the EMG power described in our previous paper [13].

Waveforms of the Hamstring Muscle Group

In contrast to the QF muscles, the individual and the group waveforms of the HAM muscles were not superimposed to each other in both temporal and spatial aspects.

The PC_1-scores captured 34.5% and 27.9% of the waveform variance in the ST and BF activation (Fig. 3B and D, solid lines). The PC_1-vectors showed the intensity exchange that occurred between the pre heel strike period (-200 ms to -50 ms) and the period from -50 ms to +100 ms illustrated in Figure 2B and D with solid arrows. The influence of positive plus negative PC_1-scores is depicted in Figure 4D-E: Positive PC_1-scores were representative for high pre activation in the early pre heel strike period and minimal post activation, whereas negative PC_1-scores led to increased muscle activation early before and early after heel strike. Thus, the results of the PC_1-vectors of ST and BF showed an exchange of muscle activity between the early pre heel strike period and the period from -50 ms to +50 ms, as found in the QF muscles.

The PC_2-scores of ST and BF explained 15.3% and 16.7% of the total variance (Fig. 3B and D, dashed lines). Both PC_2-vectors were linked with a relationship between the intensities in the late pre and the early post heel strike period as illustrated in Figure 2B and D with dashed arrows. The PC_2-vector of BF had a similar shape as those of the QF muscles. Positive PC_2-scores for the ST indicated muscle activation during the last 200 ms before heel strike and reduced muscle activation after heel strike. Subjects with negative PC_2-scores show a pronounced valley shortly before heel strike and a well pronounced bimodal peak in the early post heel strike period as illustrated in Figure 5D. Positive PC_2-scores in BF led to the maximal activation in the last 50 ms before heel strike. Nevertheless, this maximal activation was shifted to the right, the more negative the PC_2-score was (Fig. 5E).

Consequently, the results of the PC_1-vectors of ST and BF indicated that individuals mainly vary in how they balance their muscular activation during the early pre heel strike period and during the period around heel strike. The PC_2-vectors of the HAM muscles showed an exchange between muscle activation in the late pre and the early post heel strike period.

Within- and Between Muscle Group Relationship

The correlations within both the QF and within the HAM muscle group were highly significant ($p < 10^{-9}$) for both the PC_1- and the PC_2-scores (Fig. 6). What's more, the muscles within a muscle group seem to play basically the same role, independently of the subject. In contrast, there were a weak, yet significant positive correlation between VM and ST for the PC_1-scores and weak negative correlations between RF and BF as well as between VL and BF for the PC_2-scores; thus, an interaction between muscles that are either medially or laterally in close contact to each other on either side. These findings highlighted that subjects scoring positively in PC_2 for RF or VL and negatively in PC_2 for BF had a pronounced pre activation with a reduced first post heel strike activation in RF and VL and a reduced pre activation combined with a pronounced post activation in ST and vice versa for subjects scoring negatively for RF and VL, but positivley for BF. Hence, the whole time frame around heel strike is covered with acivated muscles through these interplays in PC_2 between muscles from the lateral side. Contrary for the weak positive correlation between the PC_1-scores of VM and ST, subjects with positive scores in VM showed pre activation with a reduced post activation in the first 50 ms after heel strike. Such a VL activation pattern is combiend with an increased activation between -200 ms and -100 ms as well as a reduced activation around heel strike for ST and vice versa for subjects scoring negatively. No interactions between the residual muscle pairs were observed for the first two PCs (Fig. 6).

These fingings, taken together with the strategies – high pre or high post activation – found by interpreting the PC-vectors highlighted that there exists hybrids in activation strategies that are either closer to high pre activation or high post activation.

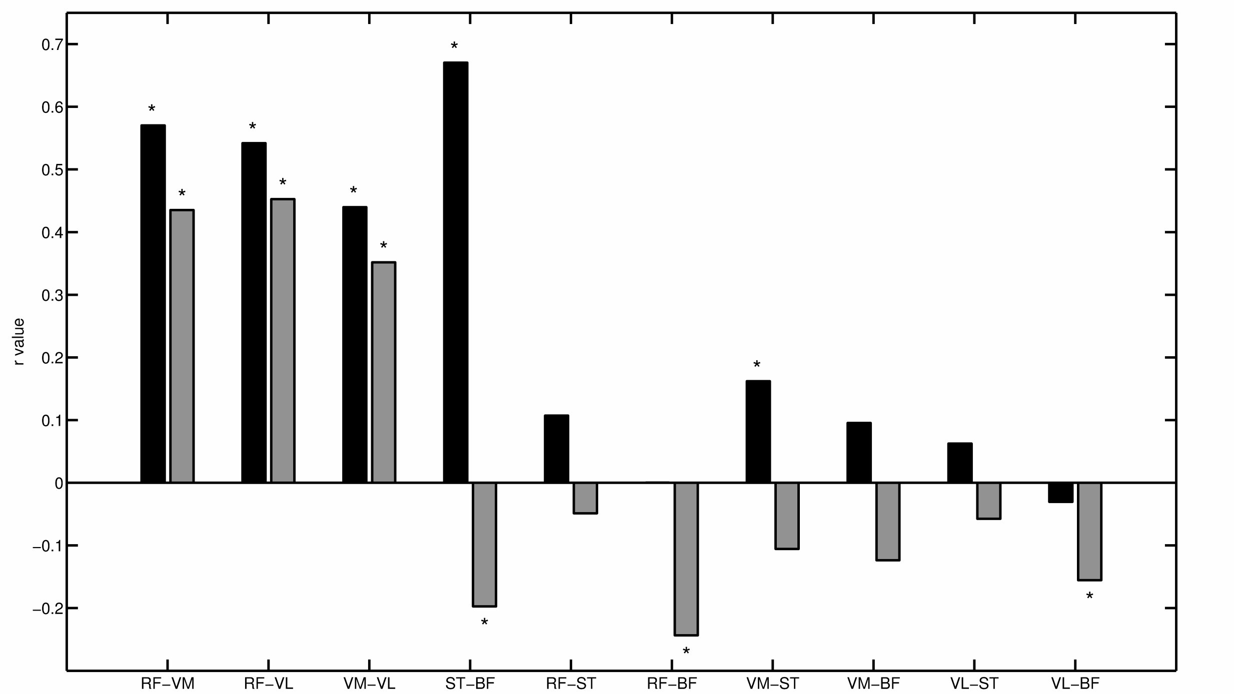

FIGURE 6. Magnitude of the correlation coefficient *r* (y-axis) between the PC_1- (black bars) and PC_2-scores (grey bars) ($n = 180$) of 10 muscle pairs (x-axis) are shown. Statistical correlation ($p<0.05$) between a muscle pair is indicated with asterisks.

Discussion

Confirming the Strategies and Subdivision in Three Parts

This study set out to identify neuromuscular activation strategies used by different subjects while walking. The activation strategy of a muscle leading to the measured waveforms could be explained in three parts: (i) the group waveform reflecting the general activation patterns used by all subjects while walking, (ii) two common strategies reflected by the PC_1- and PC_2-vector showing subject-specific deviations from the group waveform, and (iii) an unresolved, more random activation pattern reflected by higher-order PC-vectors, which could not be further resolved (Fig. 1). Therefore, as hypothesised, there were detectable strategies that influenced the amplitude of the peaks and valleys of the waveforms. The peaks and valleys seemed to be closely related to the raster shown by the grey background in Figures 4 and 5, which might be attributed to the Piper rhythm [7, 13, 30, 32]. The results show, that the neuromuscular control of the general activation pattern is modulated by two defined strategies that are recruited in a subject-specific way. The subject-specific pattern might be the cause of preferred movement [25]. To our knowledge, we are unaware of any current literature that investigated and analysed the neuromuscular behaviour in muscles surrounding the knee joint by using a wavelet-based PCA. Moreover, the PCA approach on EMG signals has previously allowed extracting information about the neuromuscular processes [4]. It was possible to extract real physiological information about the nature of the coordination of a movement [1]. However, combining the time-frequency analysis with the PCA allowed resolving a more differentiated neuromuscular strategy that was used to control and stabilise the gait pattern.

Simultaneous Control of Muscles

Movements, like walking, require the coordination and control of multiple muscles in a specific sequence of events occurring at precise time points [39]. Nevertheless, the present study was limited to a few dominant thigh muscles. Because muscles are used for both, locomotion and joint stability [28], it is often a challenge but not always possible to discriminate these two tasks.
For the QF muscles, the high degree of synchronised co-activation (Fig. 2A, C and E) and the lack of muscle-specific differences between the first two PC-vectors (Fig. 3A, C and E) reflects the fact that, on average, RF, VM and VL were recruited by a similar activation pattern, differing only slightly just before and after heel strike. Besides, synchronised activation of these muscles seems to be controlled primarily by modulating the amplitudes of the peaks and valleys within the raster shown in Figure 4A, C and E and Figure 5A, C and E.

In addition, muscle pairs within a muscle group seem to be controlled (Fig. 6). This quantified the visual detected similarity between the muscle activation patterns of QF [13]. It might be that, around heel strike, such an active within-muscle group control is a physiological modification mechanism to secure the knee on loading. Furthermore, the weak correlations between any muscle from the QF and any muscle from the HAM muscle group occurred only between muscle pairs, which are either medially or laterally, respectively. These interactions were unexpected results, but showed that there is additionally to the within-muscle group and within-muscle controlling, a mechnism that may control the knee rotation and maintaining joint stability.

The Strategy of Mm. Quadriceps Femoris: The Balance Between pre and post heel Strike Activation

As seen in Figure 2A, C and D to Figure 5A, C and E, the different strategies include a trade off between pre and post heel strike activation. This was already observed as a major gender difference [38]. Especially at heel strike, where the human locomotor system is affected by irregular impact forces, controlled muscle activation patterns are essential for counteracting the destabilising forces to keep the knee joint stable. The effect of the first two PC-vectors of the QF muscles explained that most of the variability was caused by a balancing mechanism of muscle activation between the pre and the post heel strike period. The muscle activation coupling, identified with the PCA approach, could be viewed as a response to a relationship of preparatory action before ground contact (pre activation) [5] and a pre-programmed adaptive reflexive action (post activation) [13]. These results confirmed the findings of the existence of a muscle tuning process, where the muscular structure has to be well prepared in order to act on the impact forces [26, 40]. The level of such a neuromuscular modification depends on various factors. For example, by varying exterior conditions (e.g. shod vs. barefoot), it was possible to detect in EMG signal changes in timing, frequency, and intensity content occurring in the last 50 ms before and the first 50 ms after ground contact in lower leg muscles [39, 40].

The reconstructed individual waveforms of the QF muscles, using the first two PC-vectors only, revealed that individuals verified a transfer between two distinct behaviours (Fig. 4A-C) during the time window of 200 ms before and after heel strike. 1): High pre and low post heel strike activation and 2) low pre and high post heel strike activation. The functional reason why individuals prefer strategy #1 or #2, isn't clear, but both strategies may stand in relation to the impulsive force around heel strike. In the past, Radin et al. [29] has reported that the eccentric activated QF muscles can inhibit the occurrence of harmful impulsive forces at heel strike and the risk of joint damages can thus be minimised [17]. Such an active activation pattern may correspond to strategy #1. An impairment of such an active muscle control before heel strike may lead to increased post heel strike muscle activation that counteracts the destabilising impulsive force, as detected in strategy #2.

We suppose that such an appropriate timed and balanced activation pattern found in the QF muscles is one of the key effects supporting an active functional muscle control.

The Strategy of the Hamstring Muscles: Shift from pre to post heel Strike Activation

Around heel strike, the HAM muscles mainly decelerate the leg from the swing phase [28] and provide dynamic stability to the knee [2]. In spite of similar main function while walking, the activation patterns of the ST and BF (Figs. 1D-E, 2D-E) vary in shape. This isn't in accordance with the results of Hubley-Kozey et al. [15] who have recently reported highly similar neuro-muscular activation patterns while walking. Even though the activation patterns were different between ST and BF, two common activation strategies were extracted during the period from -200 ms to +200 ms: 1) High activation from -200 ms to -150 ms and low post heel strike activation and 2) high activation from -50 ms to +25 ms. Most of the variability was caused by a shifting mechanism of muscle activation from the pre to the post heel strike period. The shift in activation could be seen as a transfer of key functions from deceleration the leg at the end of swing phase to one of counteracting the knee destabilising forces shortly after heel strike [28].

The Interplay of the Muscles Stabilising the knee Joint

For subjects, it is important to prepare muscles for a safe landing because the knee joint is instable during initial contact and gets stable when the limb is loaded [28]. So a high degree of agonist-antagonist co-activation between the thigh muscles is important for maintaining an active knee joint stability [2, 14, 21, 31], but also to protect the joint from injuries [2, 24].

Although walking is a constrained movement, there is a variation in the muscle recruitment [10, 41] and certain features are present in many muscles [13, 35]. Therefore, various muscles share rhythm and/or triggering to heel strike [13] and/or activity behaviour [3, 16]. The similar strategies of the QF and HAM muscles differentiate two kinds of preparation for landing: one is using a pre impact muscle tuning and the other is reacting by a prepared post heel strike strategy. Strategy #1 leads to the speculation that the human system tunes the QF muscles shortly before initial contact. The knee joint is prepared for the expected impact. Consequently, the minimal muscle activation shortly after heel strike controls only the knee joint during the first part of the stance phase. In contrast, strategy #2 is focused on controlling the stabilisation of the knee joint in the early post heel strike period [11] through counteracting the force development immediately after heel strike.

The study shows that the neuromuscular control of a general activation pattern is modulated by two well-defined strategies, which are recruited in a subject-specific way. Any individual waveform could be explained by the combination of the group waveform, the subject-specific deviation from the group waveform that influences the amplitude of the peaks and valleys of the waveform, as well as a more random activation pattern. Thus, individuals have a constrained flexibility in how they balance their pre and post heel strike muscle activation.

CONFLICT OF INTEREST

The authors report no potential conflict of interest or the appearance of an interest conflict with regard to the study presented in this paper.

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Chapter 5

General Discussion & Outlook

Abbreviations

EMG, electromyography.

General Discussion

Although walking is a constrained movement, there is variation in the muscle recruitment patterns. The processed wavelet-based EMG signals in Chapters 3 and 4 indicated that the task structure contained in walking doesn't prescribe one single neuromuscular strategy, and that multiple configurations of muscle activation can result in functionally equivalent postural control, as Hof had already predicted in a simulation study [9]. By applying a principal component analysis approach, the intra-muscular analysis of EMG signals while walking has shown that any activation pattern is a combination of (i) the group activation pattern used by all individuals, (ii) two common strategies – either a pre impact muscle tuning or a post heel strike reaction – showing the subject-specific deviations and (iii) an unresolved, more random activation pattern. Suggestions that individuals have a constrained flexibility in how they balance their pre and post heel strike muscle activation. The functional reason why individuals prefer either a pre or a post heel strike activation isn't clear, but they may differ in the manner in which they counteract the destabilising impulsive loading force occurring around heel strike. To unravel the reason for any of these strategies, one needs more EMG patterns and additional information about mechanical parameters, e.g. walking patterns, body weight and the forces occurring at heel strike in order to correlate these parameters with the EMG patterns.

Especially at heel strike, where the human locomotor system is affected by irregular impact forces, controlled muscle activation strategies, "rapid central processing and accurate motor control of strong muscles" are essential for counteracting the destabilising forces and thus for keeping the joint stable [11]. The precisely timed co-activation of *Mm. quadriceps femoris* and *M. semitendinosus* – visible in the multi-raster plot described in Chapter 3 and quantified in more detail by applying a principal component analysis in Chapter 4 – is important for a mobile, but stabile knee joint. A balanced activation of *M. vastus medialis* and *M. vastus lateralis* is furthermore required to control the translation of the patella [3, 12, 13], and to maintain the dynamic stability of the patellofemoral joint. In addition to a high intra-muscular coordination found while walking, a significant inter-muscular interplay between muscles of the same muscle group and between muscles either on the medial (between *M. vastus medialis* and *M. biceps femoris*) or on the lateral side (between *M. vastus lateralis* and *M. semitendinosus*) of the knee has been found. Such interactions were unexpected results, but showed that, in addition, to the within-muscle and within-muscle group controlling, there is a mechanism regulating the knee rotation and the fine tuning of muscles in order to control subtle changes in the interplay of structures surrounding the knee joint due to destabilising forces to gain a stable knee joint. This is in agreement with other researchers who have proposed that co-activation is protective and that it acts to stabilise a joint [1, 6].

The mechanism underlying neural control is complex, wherein typical temporal characteristics, such as rhythm at about 40 ms within the EMG signal or triggering to heel strike of peak activations while walking were structures occurring independent of the subject, muscle, task and condition (Chapters 2 and 3). In view of the fact that individuals share these properties, there seems to be good reasons that temporal features play an integral role within the neuromuscular control mechanism. Furthermore, the temporal relationship of peak intensities shows that few individuals applied a strictly paced and controlled pattern and the majority of them a more randomly arranged activation pattern. It isn't clear what circumstances have contributed to such a high level of inter-step repeatability of muscle activation. Differences in consistency in the activation patterns between steps may reveal changes in the neuromuscular control strategy and these variations may be responsible for the separability of the EMG spectra between endurance- and sprint-trained athletes in Chapter 2. A high consistency in the activation patterns could be typical for sprint-trained athletes with an increased ability to synchronise motor units – among others – by strength training [15] whereby strength gain can be achieved without structural changes in a muscle but not without neural adaptations [5]. It isn't completely understood under what circumstances the synchronisation increases and whether synchronisation of motor unit activation produces a more forceful contraction [14]. Yet, in contrast to maximally activated muscles [21] and to running [16] where the neuromuscular rhythms are precisely controlled, walking is a constrained movement that has more degrees of freedom. Because of that walking doesn't need a tight control of muscle activity and there is variation in the muscle recruitment patterns while walking [7, 24].

Results of Chapter 2 indicate that the EMG frequency spectra change systematically with training; thus the EMG signals mirror the functional state of a muscle as a component of the state of the individual and allow monitoring of training-related changes in muscles. In general, it is difficult to draw any physiological and neuromuscular conclusions from the observed EMG features and to distinguish within an EMG signal the source of these alternations because both central properties as well as muscular properties influence the EMG signal in various manners [4, 25].

The results of this thesis may be suggest that rhythm, synchronicity and neuromuscular activation strategies are brain-related features, which are quantifiable by combining wavelet-based EMG signals with pattern recognition approaches. This approach provide a deeper insight into the muscular behaviour and the role of the neuromuscular control mechanisms in motor output, in general and between individuals and have increased the knowledge about the functional state of muscles that stabilise the knee joint. The various combinations in interactions of activation patterns of the thigh muscles surrounding the knee joint may be key functions to securing a stable knee joint before the occurrence of stressful events and may be a neuromuscular component of dynamic joint stability adapted to the subject-specific circumstances.

Comments on the Method

Study Design

Well-defined exclusion criteria can improve the homogeneity of a group, but variability between subjects can never be avoided. The relatively low sample size in all three studies, between seven and ten subjects, may have limited the interpretation of the results of this thesis to a certain extent and may have an effect on the power of the statistical measures.

In spite of only 15 athletes, seven endurance- and eight sprint-trained athletes (Chapter 2), a total of 15 average EMG frequency spectra were sufficient to distinguish the two groups with a recognition rate between 71% and 93% for classification of spectra of unknown subjects. A larger number of participants can define more delimited clusters for each group and, thus, can reduce the number of not assignable athletes and increase the recognition rate if the new subjects have similar properties. In Chapters 3 and 4, a total of 180 EMG patterns – 10 subjects each with 18 patterns – were analysed. A larger number of individuals may reduce the between-subject variability in the time dependence of peak intensities, and thus narrow the distribution of the inter-pulse intervals. Furthermore, the cumulative total variance of the first two principal components may increase and, therefore, the reduced EMG waveform would more strongly approximate the original waveform. Another possibility could be that the principal component analysis reveals a third activation strategy.

The effect of indirect factors, such as subcutaneous fat and muscle properties, are difficult to limit and control and can't be kept constant in surface EMG experiments.

Data Recording

Skin preparation, electrode positioning and fixation were standardised according to the SENIAM-recommendations [8] and were always executed by the same examiner. The inter-subject variation in bodily frame made the electrode placement easy for muscular subjects and more difficult for subjects with a thicker subcutaneous tissue layer. The subcutaneous tissue layer between the activated muscle fibre and the electrode affects mainly the amplitude and not the timing aspect of the EMG signal. This effect was eliminated by a normalisation procedure to power of 1.

A disadvantage of surface EMG, utilised throughout all of the studies in this thesis, is that one is unable to record the activity of muscle structure in the depth and of non-superficial muscles, and of thin muscles, like *M. gracilis*, *M. sartorius* and *M. popliteus*, which surely have an effect on the functional state of the knee joint. To gain a more complete view of muscle activity, the activation patterns of multiple EMG recording points on the same muscle were analysed to improve the temporal as well as spatial information. Our results showed that the locations of the peak activation weren't shifted between the recordings from the medial to the lateral side; thus, the muscle below the triplicate electrode pairs was activated in a similar way. In future, a study setup with a larger inter-electrode distance or multi electrode array may increase information of the whole muscular behaviour.

Signal Processing

The time-frequency analysis of von Tscharner [18] allows – in contrast to the traditional EMG analysis methods – to obtain more information about the fine structure in muscle activation [22] because the wavelet has been specified for the physiology of EMG signals and its relevant muscular events [20].

The EMG signals used for the analysis have been cut into periods either in relation to the knee angle from 60° to 30° knee extension measured with a goniometer (Chapter 2) or in relation to the heel marker by using a time frame of 400 ms centred around heel strike (Chapters 3 and 4). Errors in determination of the time of heel strike by displacement of the heel marker due to skin motion were minimal. In Chapters 3 and 4, no time-normalisation was applied on the EMG signals because the real precision of the muscular events was of interest; a point-by-point comparison of the EMG activity between steps and between subjects is only possible around heel strike. The further away from heel strike, the more variability occurred between subjects and between steps. A constant walking speed may reduce this inter- and intra-subject variability, but then a muscle activation pattern of a constrained gait would be measured.

To reduce the inter- and intra-subject variability, a normalisation to power of 1 was used, as the interest was on the power distribution in time and frequency within an EMG signal [23] and not on the information about the degree of muscle activation [10], as was the case in all three studies in this thesis. As a result, a comparison of the intensities isn't possible and can't be done with surface EMG.

Pattern Recognition

Finding the optimal classifier – one that efficiently classifies unknown patterns based on measured data – is a challenge because "one never knows whether the optimum performance has been reached" [19]. A comparison of spherical classification with a support vector machine was done in Chapter 2. Our results showed that changing from spherical classification to a linear support vector machine improved the recognition rate in most cases by 13%. Such an increase was more than von Tscharner [19] has suggested. That isn't to say that the spherical classification was a bad classifier and unable to correctly assign an unknown EMG spectrum to either the sprint- or the endurance-trained group, but the classifier was less suited for the data set.

The strength of the applied classification methods is that there is no a priori variable selection and the whole pattern contributes minutely to the final result. An advantage of the spherical classification is its simplicity compared to the support vector machine. The advantage of a support vector machine compared to other classifier methods is its generalisation performance (i.e. error rates of test sets), which is mostly equal to or better to other methods [2]. One limitation of the support vector machine approach is the choice of the appropriate kernel and the adjustable parameter C.

The results in Chapter 4 showed that the combination of wavelet transform and principal component analysis applied on EMG signals provides more detailed information regarding neuromuscular structures than the traditionally used spectral variables.

Conclusion

Common to all studies used in this thesis is the gain in insight into neuromuscular control mechanism by using wavelet analysis applied on EMG signals, which wouldn't have been resolvable by methods like root mean square or Fourier Transform techniques alone because of their reduction into one domain either time or frequency domain. Furthermore, the coupling of EMG-based pattern recognition approaches allows a holistic view of the muscle activation independently of the observer.

The following conclusions can be drawn from the analysis of the EMG signals of muscles surrounding the knee joint during isokinetic knee extension and during barefoot walking:

Altered EMG Signal Following Training

- Training regimes lead to systematic differences in the surface EMG spectra
- Data reduction of the EMG signal into the single variable – the mean frequency – leads to a loss of information about muscle properties
- EMG spectra allow monitoring training-related changes in muscles

Muscle Rhythmicity

- Wavelet-based analysis of EMG signals is sufficiently sensitive to detect synchronisation of thigh muscles
- Temporal relationship between the peak muscle activations occurs predominantly at times that fit a raster-like frame of about 40 ms during walking and about 80 ms during isokinetic knee extension
- Pacing rhythm was similar in all muscles across the individuals; thus, it's may a gait-related activation feature
- Neuromuscular system has the ability of adapting to an external trigger, in this case the heel strike

Muscle Coordination

- General activation patterns are modulated by two well-defined strategies, which are recruited in a subject-specific way
- Individuals may have a constrained flexibility in how they balance their pre and post heel strike muscle activation; deviation to that may harm the movement pattern, and thus, endanger the function as well as the health of the system
- High synchronisation between *M. vastus medialis* and *M. vastus lateralis* maintains the functional dynamic stability of the patellofemoral joint
- Co-activation of muscles surrounding the knee joint preserves a stable knee joint

The EMG signal contains rich information about the functional state of a muscle and can provide a solution to any muscle and neuromuscular-relevant questions. The studies in this thesis assessed rhythm, synchronicity and activation strategies in accordance with muscle activity during dynamic tasks. The results provided information on how muscles work in concert, how muscle activity is controlled within and between muscles, and what the role of the neuromuscular control mechanism in motor output is. Furthermore, one can say that individuals share muscle activation features and activity behaviours, such as rhythm, triggering to heel strike and pre or post heel strike activation patterns. Hence, multiple configurations of muscle activation can result in functionally equivalent movements whereby some activity profiles and activity behaviours are common in subjects independent of muscle and dynamic task. In addition, the most important aspect for a stabilising knee joint strategy appears to be a high synchronisation of *Mm. quadriceps* *femoris* with an interaction between muscles that are either medially or laterally in close contact to each other on either side.

Consequently, beyond the field of rehabilitation, sports and life sciences might benefit from the knowledge gained in this thesis due to the fact that the processed EMG signal reflects the functional state of a muscle as a component of the state of the individual. The combination of any of the techniques used in this thesis together with wavelet-based EMG lead to a useful characterisation of the muscular behaviour and the neuromuscular control mechanism to motor output.

Future work will extend the findings presented in this thesis, and will work towards a more comprehensive understanding of the neuromuscular control mechanism in relation to a stable knee joint.

OUTLOOK

The studies presented in this thesis provide novel information on the neuromuscular control in dynamic tasks, and raises a series of questions that could be addressed in future investigations. With the potential of monitoring training-related changes by EMG and using this to improve athletic development, further research is needed to answer the following questions: (i) how do EMG frequency spectra change across a time interval following training or rehabilitation (as an assessment of the training status, e.g. preparatory phase versus competition phase or before versus after rehabilitation), (ii) can an endurance-trained athlete achieve an activation pattern of a sprint-trained athlete by appropriate training and (iii) can an EMG spectra assess the predisposition of an athlete either to be a sprinter or a marathon runner? The answers to these questions are interesting for both coaches and physiotherapists because they support performance diagnostics, talent detection, monitoring of training or rehabilitation progress, and the design of effective training programs. Contrary to muscle biopsy [17] to indicate, which fibres are available and how the proportion changes over a training period, our approach is a functional non-invasive measure that improves insight into muscle properties under dynamic conditions. Hence, EMG should provide insight into the effect of an intervention or a treatment. A clinically important question is whether physiotherapy can modify or even recover the EMG structure in patients who have altered muscle activation as a function of disuse or injury.

Future work will focus on the comparison of EMG signals of different groups of subjects suffering from knee osteoarthritis, neuromuscular or neurological disorders, patellofemoral pain syndrome, or subjects before and after rehabilitation intervention and to look if – in pattern space – the different groups form single clusters, overlapping clusters or clusters with a mixture of groups. More data points in pattern space of an inhomogeneous cohort may help to interpret the reason behind the mixture of the two dominant activation strategies – the pre heel strike tuning or a post heel strike reaction – extracted using a principal component analysis.

The capacity to assess movement-related synchronicity, rhythmicity, and knee stabilising muscle activation patterns, as well as neuromuscular control strategies used by females while walking unravels the neuromuscular aspects involved in controlling motor output. For instance, monitoring differences between the control strategy of subjects with normal gait patterns and those with deteriorated neuromuscular control strategies would improve the knowledge of which mechanisms play a role in the development of these patterns. In particular, future research should focus on temporal and spatial abnormalities in muscle activation patterns in patients or athletes. In context of these results, the investigation of activation patterns while walking on uneven or unstable ground may improve the understanding of the mechanism underlying the muscular fine tuning or muscular correction strategies to keep the knee joint stable.

The results presented in this thesis require further substantiation (e.g. including muscle activation patterns of *M. gastrocnemius medialis* and *M. gastrocnemius lateralis*, another muscles affecting the knee motion), but provide support for physical activity as a potential protective factor in maintaining the health and function of the knee joint.

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List of Publications

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