Alterations in lower limb multimuscle activation patterns during stair climbing in female total knee arthroplasty patients

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Kuntze G, von Tscharner V, Hutchison C, Ronsky JL. Alterations in lower limb multimuscle activation patterns during stair climbing in female total knee arthroplasty patients. J Neurophysiol 114: 2718–2725, 2015. First published September 9, 2015; doi:10.1152/jn.00370.2015.—Total knee arthroplasty (TKA) patients commonly experience neuromuscular adaptations that may affect stair climbing competence. This study identified multimuscle pattern (MMP) changes in postoperative female TKA patients during stair climbing with a support vector machine (SVM). It was hypothesized that TKA patients adopt temporal and spectral muscle activation characteristics indicative of muscle atrophy and cocontraction strategies. Nineteen female subjects [10 unilateral sex-specific TKAs, 62.2 ± 8.6 yr, body mass index (BMI) 28.2 ± 5.4 kg/m2; 9 healthy control subjects, 61.4 ± 7.4 yr, BMI 25.6 ± 2.4 kg/m2] were recruited. Surface electromyograms (EMGs) were obtained for seven lower limb muscles of the affected limb of TKA subjects and a randomly assigned limb for control subjects during stair climbing. Stance phase (±30%) EMG data were wavelet transformed and normalized to total power. Data across all muscles were combined to form MMPs and analyzed with a SVM. Statistical analysis was performed with binomial tests, independent group t-tests, or independent group Mann-Whitney U-tests in SPSS (P < 0.05). SVM results indicated significantly altered muscle activation patterns in the TKA group for biceps femoris (recognition rate 84.2%), semitendinosus (recognition rate 73.7%), gastrocnemius (recognition rate 68.4%), and tibialis anterior (recognition rate 68.4%). Further analysis identified no significant differences in spectral activation characteristics between groups. Temporal adaptations, indicative of cocontraction strategies, were, however, evident in TKA MMPs. This approach may provide a valuable tool for clinical neuromuscular function assessment and rehabilitation monitoring.

support vector machine; wavelet analysis; pattern recognition; muscle activity; electromyography

TOTAL KNEE ARTHROPLASTY (TKA) is an effective means for reducing pain and increasing joint function in pathologies such as end-stage osteoarthritis. In Canada, a total of 57,718 acute care hospitalizations were recorded for knee replacements in 2012–2013, representing a 21.5% increase over the past 5 years (CIHI 2014). Despite successful pain management, postsurgical TKA patients commonly display alterations in joint mechanics and muscle recruitment strategies (Benedetti et al. 2003; Berti et al. 2006; Catani et al. 2003; McClelland et al. 2011; Mizner and Snyder-Mackler 2005; Noble et al. 2005; Su et al. 1998). This may be due to a combination of muscle strength loss, atrophy, and altered function (Berth et al. 2002; Huang et al. 1996; Mizner et al. 2005; Mizner and Snyder-Mackler 2005; Rossi et al. 2006). The effects of such muscular deficits may be particularly prominent in stair climbing, which is mechanically demanding (Andriacchi et al. 1980; Costigan et al. 2002) and is associated with an increased risk of injury due to falling (Nevitt et al. 1991).

Changes in the electromyogram (EMG) of lower limb muscles have revealed alterations in temporal and spectral activation characteristics both within and across muscles of the lower limbs. Coactivation patterns between antagonist muscle groups have been described and are hypothesized to be associated with attempts to improve dynamic joint stability (Noyes et al. 1992), control postoperative movement kinematics (Banks et al. 2003), and compensate for reduced muscle strength and size (Huang et al. 1996; Lewek et al. 2004b; Mizner and Snyder-Mackler 2005; Stevens-Lapsley et al. 2010). Furthermore, EMG signal amplitude and contraction frequency alterations may be observed because of muscle atrophy and related decreased motor unit recruitment and/or changes in muscle fiber type distributions (Solomonow et al. 1990; Wakeling et al. 2002; Wakeling and Syme 2002).

These observations indicate potentially complex alterations in the temporal and spectral characteristics of muscle activations due to compensatory motor patterns that affect the interplay of muscles of the lower limbs. A simultaneous assessment of changes across these domains for multiple muscles may provide clinically relevant information to characterize neuromuscular adaptations. This may enhance understanding of the interplay of muscular activation characteristics and alterations in the coordination among agonist and antagonist muscles. Wavelet-based time/frequency analysis (von Tscharner 2000) and multimuscle patterns (MMPs) are well suited to such analyses. Wavelet analysis provides a means to resolve the intensity of myoelectric signals in the time and frequency spaces simultaneously. Combining resultant intensity plots of multiple muscles in a MMP, in turn, provides an easily comprehensible means for interrogating differences across muscles. This approach has successfully revealed spectral and temporal differences of muscular activations in joint pathologies (Kuntze et al. 2015b; Nüesch et al. 2012; von Tscharner and Valderrabano 2010). Importantly, quantification of intensity pattern differences requires new computational approaches that reveal the degree of dissimilarity of pathological and healthy muscle activations. Approaches are needed that identify the specific pattern features that are altered as a consequence of musculoskeletal pathology. A variety of methods have been developed for this purpose (Enders et al. 2015; Gokgoz and Subasi 2015; Subasi 2013; von Tscharner et al.
The support vector machine (SVM) (Schölkopf and Smola 2002; Shawe-Taylor and Cristianini 2004), a vector-based supervised learning model, is particularly suited to the question of data classification and identifying specific features that are altered because of musculoskeletal pathology. Previous studies have applied a SVM to successfully delineate and group muscular activations and gait kinematics in TKA patients (Güler and Koçer 2005; Levinger et al. 2009; Subasi 2013). With a linear kernel, it is possible to calculate the discriminant vector, a vector that separates the data points in the data space (von Tscharner et al. 2013). A projection of the data points onto the discriminant vector shows an accumulation of points on either side of the separating plane, thereby identifying the points that belong to one or the other group. The SVM discriminant may in turn be visualized as a pattern of activation features that characterize the classification process (von Tscharner et al. 2013). This discriminant pattern has been used in combination with a MMP to provide a detailed description of the temporal and spectral alterations within and between lower limb muscles of TKA patients during walking (Kuntze et al. 2015b). However, there remains a paucity of information on the specific muscle activation pattern alterations in postsurgical populations during more demanding tasks such as stair climbing. Wavelet analysis, SVM, and MMP approaches offer a unique combination of methods to identify temporal and spectral changes following TKA surgery. They provide new insights into alterations of the activity and interplay among multiple muscles.

The objective of this study was to assess the temporal and spectral differences in muscle activation strategies during stair climbing across superficial muscles of the lower limb in a cohort of postoperative female TKA patients and healthy female control subjects. A combined wavelet analysis, MMP, and pattern recognition approach was chosen for the analysis in order to identify subject-specific pattern differences. For the differences to be reliable, the MMPs of control subjects and patients must be classifiable, meaning that participants can be assigned to the correct group. The hypothesis was that wavelet-transformed lower limb EMG data for TKA and healthy control subjects performing a stair climbing task can be successfully classified with a SVM. Inter- and intramuscular temporal activation differences were investigated by using the SVM discriminant to identify intensity pattern features that contributed to successful classification and to characterize pathological alterations in muscle coordination strategies. Furthermore, muscle patterns that provided successful classifications were explored for spectral alterations that may be indicative of muscle atrophy and may have contributed to successful classification.

MATERIALS AND METHODS

Subjects

Ten postsurgical (19 ± 3 mo) female subjects [TKA group; 61.9 ± 8.8 yr, body mass index (BMI) 28.0 ± 5.3 kg/m²] with a primary, unilateral, non-ligament-retaining TKA (Gender Solutions NexGen High-Flex Knee; Zimmer) and nine healthy age-matched female control subjects (CON group; 61.4 ± 7.4 yr, BMI 25.6 ± 2.4 kg/m²) volunteered for this study. All but one subject underwent a nonnavigated, minimally invasive quadriceps-sparing procedure by one orthopedic surgeon, with the remaining subject undergoing a medial parapatellar procedure by a second surgeon. Participants were excluded if they had functional impairments rendering them unable to perform activities of daily living or had medical conditions and/or recent surgery affecting mobility. CON subjects were excluded if they had ever undergone surgery on the lower limbs, experienced consistent joint pain, or had conditions that adversely affect mobility. Ethical approval was obtained from the local ethics board (ID no. 21170), and informed consent was obtained from each subject before testing.

Study Protocol

Following recommendations by SENIAM (www.seniam.org), EMGs of seven lower limb muscles of the affected limb of TKA subjects and a randomly assigned limb of CON subjects were recorded. Small patches of skin were shaved and cleaned with rubbing alcohol, and bipolar Ag/AgCl EMG electrodes (diameter 10 mm, interelectrode distance 20 mm; Noraxon) were placed on the skin overlying the lower extremity musculature. Muscles of interest included vastus lateralis (VL), vastus medialis (VM), rectus femoris (RF), sartorius (SAR), semitendinosus (SEMI), biceps femoris (BF), lateral gastrocnemius (GAS), and tibialis anterior (TA). EMG signals were preamplified (Biovision), electronically band-pass filtered (10–500 Hz), and sampled at 1,200 Hz. After a task familiarization to identify each subject’s preferred pace, subjects performed 10 stair ascends using a custom-built five-step instrumented staircase (tread 280 mm, riser 190 mm). Forceplates (OR6-6, AMTI; 9286AA, Kistler Instrumente) were integrated in steps 2 and 3 of the staircase, and a handrail was provided for support. Timing lights (Multi-Beam, Banner Engineering), positioned in front of the first and last steps (between-gate distance 1.12 m), were used to provide feedback on the subjects’ pace. Subjects were instructed to approach and ascend the staircase at a comfortable pace without using the handrail. No instructions were provided regarding which limb to use first for stair ascent. All trials were conducted barefoot.

To accurately assess subject-specific stair ascent velocities for data analysis purposes, an eight-camera three-dimensional (3D) motion analysis system (Motion Analysis) was utilized. This eliminated potential inaccuracies in timing light measures due to differences in stair width, number and stair ascent velocities and provided a measure of stair ascent velocity only. Reflective marker spheres were attached to the left and right anterior superior iliac spines (ASIS) as well as the left and right 5th metatarsals (ASIS) as well as the left and right 5th metatarsals (ASIS) as well as the left and right 5th metatarsals (ASIS). Velocity was determined as the change in the horizontal position of the ipsilateral ASIS marker from contact of the foot with the second step to consecutive contact of the opposite foot with the fifth step. This approach resulted in a measure of ASIS displacement with time (velocity in m/s) over two alternating strides. Ground reaction force (GRF) data were sampled at 1,200 Hz, and 3D marker data were sampled at 120 Hz.

Data Analysis

Time normalization and wavelet analysis. EMG data for the stance phase of gait were identified using the synchronously collected GRF data. A force cutoff value of 2% peak vertical GRF was used to identify heel strike (HS) and toe-off (TO). To this period an additional 30% of stance was added to both sides to include muscle activity that occurred prior to HS and after TO. Thereafter, the entire time period (i.e., 160% of stance) was wavelet transformed using 10 nonlinearly scaled wavelets (w) with center frequencies of 19–395 Hz (von Tscharner 2000). Wavelet-transformed EMG intensity data were time normalized by subdividing each data series into 501 time points. Consequently, the EMG intensity matrices were of equal size (10 × 501). Data visualization with contour plots and data processing was performed using intensity patterns of the intensity (square root of the power extracted by the wavelet transform) of a muscle contraction over normalized time (x-axis) and at each wavelet (y-axis).
All EMG data were visually inspected for noise such as motion artifact that may have been introduced during the dynamic movement task. Conforto et al. (1999) observed that such artifact may occur within frequency ranges covered by \( w_1 \) in the wavelet domain. To ensure pattern discrimination based on noise free EMG signals, \( w_1 \) was removed from the wavelet pattern and all data displaying signs of signal noise were removed before running the SVM. This process resulted in the inclusion of five selected clean trials per subject that were taken further for analysis.

**SVM classification.** To facilitate the investigation of time and frequency domain differences, the mean intensity patterns of the five selected trials were computed for each subject. Mean patterns were normalized to the total power of the muscle activation. Total power was equal to the sum of intensities of \( w_{2-10} \) across the entire activation period. This approach minimized between-subject differences in activation intensities inherent to dynamic EMG recordings. Resultant normalized subject data were transformed into one-dimensional data vectors containing the intensity data over time at each wavelet band in ascending order from \( w_2 \) to \( w_{10} \) for each investigated muscle. Subject vectors were combined in a data matrix that acted as input for SVM classification.

SVM classification was performed in MATLAB (v2014b, Statistics Toolbox, The MathWorks) with a linear kernel following the approaches summarized by von Tscharner et al. (2013) (Fig. 1). A SVM determines the maximal margin around a classification boundary (hyperplane) that separates linearly separable data such as the data of two distinct groups. SVM training therefore provides a subset of data, the support vectors, that fully describe the discriminant function used for data classification. New data can in turn be tested against this discriminant function to assign the data to one of two groups. The fraction of correctly classified data can be determined and yields a discriminant function to assign the data to one of two groups. SVM training reduces a high-dimensional data set to a hyperplane and its corresponding set of support vectors. The resultant linear SVM discriminant may be used for binary classification of newly introduced data (testing data). Here, information on the hyperplane vector normal (\( W \)), the distance of the hyperplane normal to the origin (\( b \)), and the distance of the testing data to the hyperplane is used for the classification process, where data on either side of the hyperplane may be either +1 or −1 (i.e., group A or group B).

![Fig. 1. Visualization of the support vector machine (SVM) analysis approach.](http://jn.physiology.org/)

A hypothetical data set, group A and group B, is presented. During SVM training, the algorithm determines the location of a separating hyperplane (solid line) that maximizes the margin (dashed lines) between data points of opposite groups. The points that define the location of the hyperplane and its margins are termed the support vectors. Therefore, SVM training reduces a high-dimensional data set to a hyperplane and its corresponding set of support vectors. The resultant linear SVM discriminant may be used for binary classification of newly introduced data (testing data). Here, information on the hyperplane vector normal (\( W \)), the distance of the hyperplane normal to the origin (\( b \)), and the distance of the testing data to the hyperplane is used for the classification process, where data on either side of the hyperplane may be either +1 or −1 (i.e., group A or group B).

EMG data, while maintaining the requirement that no data of a test subject be present in the training data set.

Because the SVM considers all information available in an intensity pattern, signals of low intensity, such as those due to residual muscle activity, may lead to classification despite lacking an apparent functional significance. To investigate the influence of low-intensity signals on the recognition rate of each muscle, an iterative thresholding technique was used that removed intensities between 0 and 10% maximum intensity at 0.1% increments. At each threshold level the fraction of correctly classified intensity patterns was computed for each muscle to determine the muscle-specific threshold level resulting in the highest recognition rate.

The assessment of the specific intensity pattern features that contributed to significant recognition rates was based on the calculation and visualization of the SVM discriminant. Since the SVM discriminant itself is a vector in this space it can be displayed as a pattern. The SVM discriminant pattern was displayed as a contour plot with features unique to the TKA group in red and features unique to the CON group in blue. Areas with no discernible differences between groups were presented as white. The SVM discriminant pattern was recovered using information of the support vectors and the corresponding weight factors provided by the SVM analysis software (von Tscharner et al. 2013). The general discriminant function is given by

\[
f(x) = \sum y_i\alpha_iK(x, x_i) + b
\]

where \( f \) represents the number of support vectors, \( y_i \) is the target value of the support vector \( x_i \), the \( \alpha_i \) are the weight factors of the support vector \( x_i \), the constant \( b \) is a bias, and \( K(x, x_i) \) is the kernel function (Bishop 2007; Theodoridis and Koutoubramas 2008).

**Temporal and spectral characteristics.** Temporal and spectral characteristics of MMPs were visually assessed using the mean group MMPs and the discriminant pattern. Further analysis of frequency domain changes was performed with the total intensity (TI) of muscle activations (normalized to total power) across specific frequency bands (\( w_{2-4} \), \( w_{6-8} \), and \( w_{10} \)):

\[
TI_{w_{a-b}} = \sum_{w_a} \sum_{w_b} \frac{WP}{t_i}
\]

where \( WP \) is the signal intensity, \( t_i \) is the time period of interest, and \( w_{a-b} \) determines the wavelets of interest.

The time period of interest was specified for each muscle to ensure consideration of the primary muscle activity only. Selected time periods for each muscle were consistent across subjects.

**Statistics**

A binomial test with equal probability for classifying intensity patterns as belonging to one or the other condition was used to determine the statistical significance of the recognition rates. The minimum number of subjects that had to be correctly classified (\( n = 13 \) or 68.4%) was computed with the function CRITBINOM in Excel (Microsoft, Redmond, WA) at a confidence level of 95%. All data were tested for normality with the Shapiro-Wilk test in SPSS (v22, IBM, Armonk, NY). Between-groups differences were investigated with either independent groups \( t \)-tests or nonparametric Mann-Whitney \( U \)-tests in SPSS (\( P < 0.05 \)). \( P \) values were adjusted for multiple comparisons with the Benjamini-Hochberg approach (Benjamini and Hochberg 1995) at a false discovery rate (FDR) of 5%.

**RESULTS**

No significant differences in mean stair ascent velocities were observed (TKA 0.43 ± 0.04 ms\(^{-1}\); CON 0.45 ± 0.07 ms\(^{-1}\); \( P = 0.56 \)) between groups.

SVM recognition rates are summarized in Fig. 2. Statistically significant recognition rates, according to a binomial
threshold of 68.4%, were observed for SEM (73.7%; 0% thresholding), GAS (68.4%; 0% thresholding), BF (84.2%; 4.8% thresholding), and TA (68.4%; 1.2% thresholding). Iteratively increasing the threshold levels altered the trajectory of the recognition rate curves for muscles with significant classification rates (Fig. 2). BF and TA displayed increasing classification rates with increasing threshold levels up to a threshold level of 5.8% and 2.0%, respectively. Further increases in threshold levels caused recognition rates to fall below the binomial threshold level. In contrast, SEM and GAS displayed more immediate decreases in classification rates with increasing threshold levels, falling below the binomial threshold at comparatively smaller threshold levels (0.7% and 0.1%, respectively). These observations indicate that BF and TA intensity pattern differences may be based on unique and comparatively high-intensity features. Classification of SEM and GAS in turn may have been based predominantly on lower-intensity data, in line with prolonged muscle activation.

Alterations in temporal activation characteristics were observable in the discriminant patterns of BF, SEM, GAS, and TA (Fig. 3). TA intensity patterns in CON subjects displayed two primary activity regions occurring before HS and after TO. TA activation was observable until midstance and terminated at the point of GAS activation. In TKA subjects an activation of TA was observable in late stance that coincided with GAS activation. This activation feature is represented in the discriminant as a red pattern, indicating its association with the TKA group. The discriminant pattern of GAS displayed few discernible features during the primary activation that were related to either the CON or TKA group. Red discriminant patterns prior to HS and after TO indicate that these comparatively low-intensity activation periods were important for subject classification purposes. This was in line with the SVM classification results showing a strong dependence of recognition rates on low-intensity data. SEM intensity patterns for TKA subjects displayed a unique activation pattern at midstance, observable

Fig. 2. Change in SVM recognition rates for muscles of interest (y-axis) with increasing threshold magnitude (x-axis). Data on left display results for muscles showing no significant classification rates. Data on right show results for muscles that displayed significant classification rates. The binomial test threshold value for significant recognition rates (68.4%) is indicated by the solid horizontal line. VL, vastus lateralis; VM, vastus medialis; RF, rectus femoris; BF, biceps femoris; SEM, semitendinosus; GAS, lateral gastrocnemius; TA, tibialis anterior.

Fig. 3. Multimuscle pattern (MMP) showing group mean intensity patterns (blue, low intensity; red, high intensity) for control (CON; left) and total knee arthroplasty (TKA; center) subjects during stair climbing. Intensity patterns are presented as contour plots with ascending order wavelets on the y-axis and normalized time [heel strike (HS) to toe-off (TO) ± 30%] on the x-axis. CON and TKA intensities were raised to the power of 0.1 to highlight areas of low muscle activity. Data for successfully classified muscles are presented at threshold levels that resulted in the highest recognition rate. Respective discriminant patterns (right) for each muscle display features unique to CON (blue) and TKA (red) groups.
as a red pattern in the discriminant. A distinct temporal switching between TKA and CON group muscle activations was observable in the discriminant pattern of SEM and BF in late stance. Following the distinct TKA pattern at midstance, the CON group displayed a unique activation pattern that terminated at TO. A period of activity was then observable for TKA subjects from TO until early swing. The activity and discriminant patterns for BF closely matched those of SEM, reflecting the likely high degree of synchronization of these agonistic muscles.

Results for EMG spectral characteristics are summarized in Fig. 4. No significant differences in spectral characteristics were identified.

DISCUSSION

The findings of this investigation supported the hypothesis that wavelet-transformed lower limb EMG data for TKA and healthy control subjects performing a stair climbing task can be successfully classified with a SVM. Combining a SVM with an iterative thresholding approach resulted in significant recognition rates for BF, SEM, GAS, and TA muscles. In contrast, significant recognition rates were not achieved for the muscles of the quadriceps group. Muscle pattern differences appeared to be attributable predominantly to alterations in the temporal domain, with no observable differences in the investigated spectral domains. The present findings therefore indicated that, during a stair climbing task, hamstring and shank muscle EMG intensity patterns provided information that allowed for a significant linear SVM classification of TKA and CON subjects. In contrast, quadriceps muscles did not provide information that allowed for successful classification, indicating few consistent activation differences for these subject groups during the chosen movement task.

Iterative thresholding, the removal of low-level intensities from wavelet-transformed EMG patterns prior to SVM training and classification, modified the trajectories of SVM recognition rates with varying effects on different muscles. Thresholding eliminated background signal noise, likely due to the electronics equipment, electrode-skin interface, and incomplete muscle relaxation. Such noise has been shown to be broadband in nature, with an RMS value equivalent to ~3% of the EMG amplitude corresponding to a maximum voluntary muscle contraction (Clancy et al. 2002; Clancy and Farry 2000). BF and TA recognition rates increased 5.3% and 15.8%, respectively, when the threshold level increased to 4.8% and 1.2% (Fig. 2). In contrast, no thresholding was required for SEM and GAS to provide significant recognition rates, with increasing threshold levels resulting in a decline in recognition rates. SEM recognition rates decreased less rapidly than those of GAS, remaining above the binomial threshold up to a threshold level of 0.7%. In contrast, a threshold level of 0.1% resulted in an immediate drop in GAS recognition rates below the binomial threshold level. These observations indicate that the classification of different muscles was likely influenced by different feature characteristics of the respective intensity patterns. BF and TA pattern classifications may have been due to relatively high-intensity features, while SEM and GAS classification was likely due to comparatively low-intensity features. The iterative thresholding approach therefore provided a means to characterize muscle-specific neuromuscular adaptations and to distinguish between distinct high-intensity and more subtle low-intensity muscle activity alterations. Here, high-intensity features may have been due to unique muscle activations, while low-intensity features may have been due to prolonged muscle contraction or indeed subtle alterations in the motor control pattern (e.g., the cortical drive) (Enders et al. 2015; Kuntze et al. 2015a; Maurer et al. 2013). However, a full understanding of the intensity pattern features that contributed to successful classification and the underlying alterations in neuromuscular control requires an investigation of the mean intensity patterns and corresponding SVM discriminant pattern.

An investigation of the specific intensity pattern features that contributed to significant recognition rates was feasible in this study because of the application of a linear SVM kernel. This approach allowed for the calculation and visualization of the SVM discriminant. The SVM discriminant pattern contained the information of the signal features that contributed to the classification of subjects as belonging to either the TKA or CON group. These data could in turn be color coded, with features unique to the TKA group in red and features of the CON group in blue (Fig. 3). Subjects of both CON and TKA groups displayed two primary regions of TA activity occurring prior to HS and after TO. In line with observations by Benedetti et al. (2003) and Childs et al. (2004), TKA subjects displayed a further pattern of TA activity at midstance that coincided with the simultaneous activation of GAS. The likely contribution of this TKA-specific intensity pattern to SVM
classification was evident from the corresponding mean discriminant pattern, where it could be identified as a distinct red (i.e., TKA) feature. Such cocontraction of TA and GAS likely indicates an attempt by the neuromuscular system to stiffen the ankle joint in late stance. Such joint stiffening is typical for TKA patients and is thought to be necessary to counteract joint stability deficiencies (Lewek et al. 2004a). Long-term maintenance of this strategy and resultant aberrant loading of the soft tissues of the ankle joint may, however, contribute to progressive joint degeneration. It is interesting to note the apparent temporal synchronization of TA and GAS intensity patterns prior to HS and TO in TKA subjects. During late stance it can be observed that consecutive high-intensity peaks of TA and GAS appeared to occur at the same time and that the activity of both muscles ceased in synchrony prior to TO (Fig. 3). Furthermore, prior to HS, TKA subjects appeared to display a reduced activity of TA that coincided with an activation of GAS. These observations may be regarded as supporting evidence for a finely controlled cocontraction process that may optimize synchronous force production by antagonist muscles (Kuntze et al. 2015b; von Tscharner and Valderrabano 2010). These data further appear to visualize the effects of reciprocal inhibition between ankle extensors and flexors (Petersen et al. 1999) and highlight changes that are likely the result of TKA.

GAS displayed the greatest sensitivity to iterative thresholding, which may be seen as an indication that differences between CON and TKA subjects were small. Given the time period of recovery since surgery (~19 mo), these observations appear to support those of Benedetti et al. (2003). Benedetti et al. describe a GAS activation following arthroplasty that was characterized by low-intensity activations prior to and after the primary muscle contraction in late stance. The authors describe a continual decrease in this pattern abnormality over time up to 24 mo after surgery. It is therefore feasible that some of the subjects in the present TKA cohort displayed a GAS activation that recovered sufficiently to fit the patterns of healthy control subjects. Longitudinal studies of GAS muscle activity alterations following surgery and with rehabilitation would be helpful to identify the progression of functional recovery. This is of particular interest in combination with measures of balance that indicate that altered neuromuscular control may lead to abnormal postural stability (Baltich et al. 2015). The thresholding approach implemented in this study may indeed be a useful tool to quantify the progression of recovery by using the reduction of low-intensity activations as an assessment criterion.

SEM and BF displayed similar temporal intensity patterns throughout the time period under investigation. This reflects a tight synchronization of intensity peaks of these agonist muscles. Such synchronization during dynamic muscular contractions has previously been reported for quadriceps and hamstring muscles during walking (Huber et al. 2011). Huber et al. described a pacing of intensity peaks of ~40 ms that is hypothesized to coordinate agonist and antagonist muscles to regulate muscle stiffness during the absorption of impact forces. The discriminant patterns of the TKA group further revealed a prolonged activation of SEM and BF at the end of stance and continuing into early swing. This was preceded by a distinct temporal switching between TKA and CON subjects from midstance to TO, in line with observations for BF during walking (Kuntze et al. 2015b). These observations indicate an aberrant activation onset of SEM and GAS at midstance by the TKA group compared with CON subjects, who displayed a primary activation in late stance that terminated at TO. This activation onset shifted hamstring activations to coincide with quadriceps muscle activation. Quadriceps and hamstring muscle dysfunction (Stevens-Lapsley et al. 2010) and muscle weakness likely contributed to the occurrence of such cocontraction (Hubley-Kozey et al. 2008). Synchronous activation of these antagonist muscle groups in turn may provide a means to control abnormal knee prosthesis kinematics (Banks et al. 2003) and play a role in the augmentation of stresses on knee prostheses (Harman et al. 2001). These data therefore provide supporting evidence for the continued altered neuromuscular control of hamstring and quadriceps muscles in TKA groups undergoing non-ligament-retaining arthroplasty. Further research is needed to identify whether it is feasible to modify these neuromuscular compensation strategies through rehabilitation, exercise, and alterations of the surgical approach. Cruciate ligament-retaining or unicompartmental approaches may indeed contribute to the creation of an intrinsically more stable knee joint that reduces the requirement for joint stabilization with cocontraction and reduces mechanical implant deterioration (Banks et al. 2003). However, the in vivo neuromuscular consequences have yet to be established in detail.

The data presented above provide evidence that pattern recognition tools combined with novel MMP visualization approaches provide meaningful information on muscle activation differences between healthy control subjects and populations with joint pathologies. Interestingly, no alterations in the spectral characteristics of activations of lower limb muscles were evident. Previous investigations of walking indicated that end-stage ankle osteoarthritis populations display reductions in high-frequency content of TA and GAS (Valderrabano et al. 2006). Such alterations were related to muscle atrophy (Valderrabano et al. 2006) and remained evident over a prolonged time period (Valderrabano et al. 2007). Within the context of stair ascent, however, it appears that changes in the temporal domain played a key role in classifying CON and TKA EMG intensity patterns. However, it is not feasible from the present data to discern whether these differences resulted from previous joint pathology (e.g., end-stage osteoarthritis) or TKA surgery.

It is important to recognize the effects of the relatively low cohort sample size of this study. Given the resultant limited power, any observations close to the set level of significance may positively or negatively impact the validity of the conclusions being drawn. Furthermore, it is important to recognize the potential influences of both aging and individual recovery rates after surgery on muscle activation characteristics. This study utilized a healthy control cohort of elderly subjects, and it may be that not all subjects displayed normal activation patterns, thereby reducing the recognition rates. Similarly, some TKA subjects may have recovered normal muscle activation patterns more readily than others and would therefore no longer be classifiable as TKA. Consequently, larger cohort studies are needed to further validate the observations of this study. A larger control cohort would enable an optimization of the subjects that contribute to the healthy pattern and contribute to the optimization of SVM recognition rates.
tation was that EMG data were not normalized to a maximum voluntary contraction and that subjects performed the task at their preferred pace. As a consequence the analysis was conducted for time- and intensity-normalized data with respect to temporal and spectral domains only.

The approach presented above may provide a valuable tool in a multifactorial analysis that combines EMG assessments and biomechanical tests of gait and balance to detect pathological changes in neuromuscular control reflected in the fine structure and variability of these data. This approach enables the investigation of not only large neuromuscular alterations, such as TA-GAS cocontraction, but also more subtle alterations that may manifest in the underlying muscle activation structure. The combination of wavelet analysis, MMP, and SVM classification provided a means to quantify subject-specific, persistent, multimuscle alterations in intensity patterns that remained observable after surgery. The high temporal and spectral resolution of this approach provided the means to reveal information on the temporal characteristics of compensatory motor control strategies across agonist and antagonist muscles in this postsurgical population. Furthermore, the novel visualization of multimuscle and SVM discriminant data in a MMP provided a readily comprehensible means for data interpretation that may prove invaluable in supporting patient-clinician communication and knowledge translation.

Conclusions

Multimuscle and discriminant patterns visualized within muscle alterations and between-muscle interactions and revealed supporting evidence for a precise neuromuscular coordination of agonist and antagonist muscle activations. To ensure that the observed and discussed differences in the MMP were significant, new methodologies applying SVM to the MMP were implemented. They revealed unique EMG pattern adaptations in postsurgical TKA patients that allowed for a detailed interpretation of functional differences. In contrast to classical analysis methods, combining wavelet-based time-frequency analysis of multimuscle EMGs with SVM pattern discrimination enabled the consideration of change across the entire muscle activation pattern. The applied analysis operated in both time and frequency domains simultaneously, which was advantageous given the potential multifactorial nature of EMG signal change in musculoskeletal pathologies. Furthermore, classification of individuals, rather than consideration of the group only, may be regarded as advantageous for the purpose of assessing the subject-specific recovery process. New analysis approaches are needed based on a holistic analysis approach and readily comprehensible outcome visualization to enable effective patient assessment and longitudinal recovery monitoring.

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the author(s).

AUTHOR CONTRIBUTIONS


REFERENCES


