Gender-related differences in ankle-muscles recruitment during walking

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Abstract: Surface electromyographic (sEMG) signal is commonly used as main input information to control robotic prosthetic systems. sEMG signals vary from person to person; gender is a factor influencing this variation. Thus, the aim of the study is to detect gender-related differences in sEMG activity of two main ankle-flexor muscles [tibialis anterior (TA) and gastrocnemius lateralis (GL)] during walking at comfortable speed and cadence. Statistical analysis of sEMG signals, performed in seven male (M-group) and seven female (F-group) adults, showed clear gender-related differences in muscle behaviour. The assessment of the different activation modalities, indeed, allowed to detect that F-group adopts a walking modality with a higher number of activations during gait cycle, compared to M-group. This suggests a female propensity for a more complex muscle recruitment, during walking. This novel information suggests considering a separate approach for males and females, in providing electromyographic signals as input information to control robotic systems.

Keywords: surface EMG; statistical gait analysis; gender; ankle motion; shank muscles; tibialis anterior; gastrocnemius lateralis; walking; gait cycle; modalities of muscle activation; myoelectric activity.

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1 Introduction

Electromyographic (EMG) signal of human muscles is an important biological signal to understand the motion intention of human (Jordanić et al., 2016). Recently, the EMG signals have been used as the input information to control robotic prosthetic systems, being considered fundamental information to understand how the user intends to move (Lu et al., 2016; Tang et al., 2014). Indeed, these power-assist robotic systems are mainly activated based on the user's EMG signals which directly reflect the muscle activity levels of the user. Many examples of EMG-driven control robotic systems have been reported in literature (Kiguchi and Hayashi, 2012; Li et al., 2014; Tang et al., 2014).

The pattern recognition of EMG signal has been used for estimating the torque applied by a human wrist and its real-time implementation to control a novel two degree of freedom wrist exoskeleton prototype (WEP) (Khokhar et al., 2010). A control algorithm for single degree-of-freedom powered exoskeleton has been proposed, to be used in the process of physiotherapy and rehabilitation of the human upper limb (Mikulski, 2011). Proposed algorithm used EMG signals from single muscles as well as antagonist muscle pairs, to maximise the user's intuitive control over the exoskeleton system. He and Kiguchi (2007) and He et al. (2007) proposed a control system based on the skin surface EMG (SEMG) signals of the user for the exoskeleton robot to assist physically weak person's lower-limb motions. The skin surface EMG signals are mainly used as the input information for the controller.

EMG signals from ankle muscles seem to be frequently used as the main input information to EMG-driven control robotic systems. Zhen et al. (2007) presented a study on human ankle movement based on SEMG signals. Four types of movement were designed including maximum voluntary contraction, bending/extending, going down, and walking. At a later stage, the same group of researchers proposed a control method of an exoskeletal ankle based on SEMG signals has been presented in Zhen et al. (2008). The SEMG signals are acquired, and sent to the computer. The computer deals with the SEMG signals and generates the control orders. The control orders are passed to the motor controller which drives the exoskeleton to move. Two further control schemes to predict the amputee's intended ankle position using EMG data measured from an amputee for several target ankle movement patterns have been reported: a neural-network approach and a muscle model approach (Au et al., 2005). The authors found that both controllers demonstrate the ability to predict desired ankle movement patterns qualitatively. Ferris and Lewis (2009) developed pneumatically-powered lower limb exoskeletons for human physiology, and re-training motor deficiencies. One way to control the exoskeletons is with proportional myoelectric control, effectively increasing the strength of the wearer with a physiological mode of control. Healthy human subjects quickly adapt to walking with the robotic ankle exoskeletons, reducing their overall energy expenditure. Individuals with incomplete spinal cord injury have demonstrated rapid modification of muscle recruitment patterns with practice, walking with the ankle exoskeletons.

The EMG signals can be classified into two types, according with the place where they are acquired. The EMG signals detected from inside of the muscles are called intramuscular EMG, whereas EMG signals detected from the skin surface of the muscles are called SEMG. The extraction of intramuscular EMG signals is invasive and non-painless procedure; for these reasons, the intramuscular EMG signals are difficult to use practically. On the other hand, the SEMG signal can be extracted easily and painlessly, even if it is not so selective as the intramuscular one. User's SEMG is commonly used as main input information to the controller of exoskeleton robot to realise different fundamental applications, such as power-assist device, human-amplifier, rehabilitation device, and haptic interface (Khokhar et al., 2010; Zhen et al., 2007, 2008).

The EMG signals vary from person to person and from motor task to motor task. In addition, they differ for the same motion even within the same person. In particular, it has been shown that gender is one of the factors influencing the occurrence of the SEMG signal in different motor tasks (Malinzak et al., 2001) and during walking (Chiu and Wang, 2007; Chumanov et al., 2008; Chung and Wang, 2010). Therefore, characteristics of the SEMG signals should be carefully considered when developing a control method for exoskeleton robot or powered orthosis using EMG signals as input information. In some of these studies during walking, it has been detected a significantly higher activity of ankle muscles in the female population, compared to male one, especially in the tibialis anterior (TA) (Chiu and Wang, 2007; Chung and Wang, 2010). TA, together with gastrocnemius and soleus, are the main muscle that actuates the dorsiflexion and the plantarflexion motion of human ankle joint (Perry, 1992).

The purpose of this study was to evaluate the possible differences between males and females in the SEMG activity of TA during gait at comfortable speed and cadence, in terms of the frequency of muscle occurrence. Eventual differences in the myoelectric activity of gastrocnemius lateralis (GL), (TA antagonist muscle for ankle plantar/dorsiflexion) were also analysed, in order to achieve more complete information on ankle joint. The goal of this study was pursued by performing a statistical analysis of SEMG signal from a large number (hundreds) of strides per subject. Surface electromyography has been largely used for the assessment of the activation patterns of the ankle flexor muscles during normal and pathological gait (Di Nardo et al., 2013; Stewart et al., 2007). Moreover, the study is based on the recent availability of robust techniques for the detection of muscle activation intervals (Bonato et al., 1998; Staude et al., 2001), and specific tools for statistical analysis of walking (Agostini and Knaflitz, 2012).

2 Materials and methods

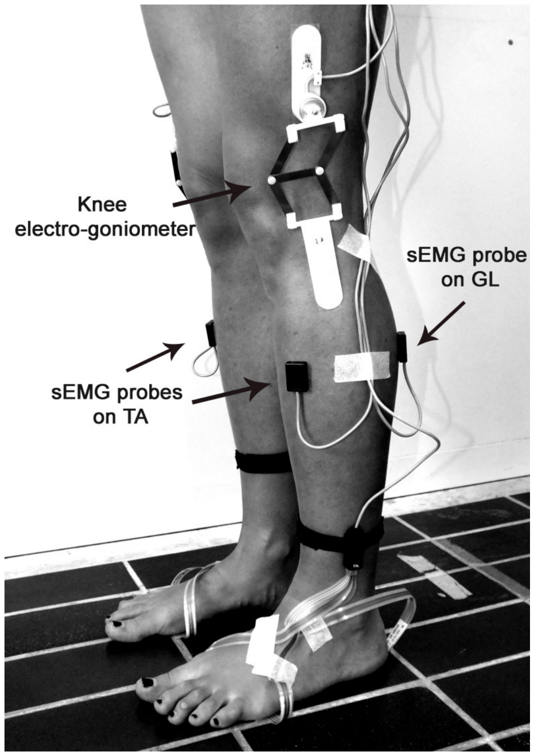
2.1 Subjects

Fourteen healthy adult Caucasian volunteers were recruited for the present study. Subjects were divided into two groups: a group of seven female subjects (F-group) and a group of seven male subjects (M-group). Mean (±SD) characteristics of the patients are: age = 23.3 ± 1.3 years; height = 164 ± 3 cm; weight = 50.4 ± 2.0 kg; body mass index (BMI) = 18.8 ± 0.7 $kg\cdot m^{-2}$, for the F-group, and age = 24.5 ± 3.0 years; height = 183 ± 7 cm; weight = 79.4 ± 10.5 kg; BMI = 22.2 ± 1.8 $kg\cdot m^{-2}$, for the M-group. Walking velocity resulted 1.17 ± 0.05 m/s and 1.25 ± 0.11 m/s for M and F group respectively. Height, weight and BMI resulted significantly different between the two groups ($p < 0.05$), reflecting physiological differences between genders, while age and velocity were not statistically different ($p > 0.05$), excluding the possible bias due to the different speed of gait on the muscular recruitment and myoelectric activity (den Otter et al., 2004). The SEMG activity during gait was recorded in both right and left lower limbs of all subjects at comfortable speed and cadence. Exclusion criteria included history of neurological pathology, orthopedic surgery within the previous year, acute or chronic knee pain or pathology, BMI ≥ 25, or abnormal gait. Abnormal gait was determined observationally by a licensed physical therapist, specialised in gait analysis. Before the beginning of the test, all participants signed an informed consent.

2.2 *Recording system: signal acquisition*

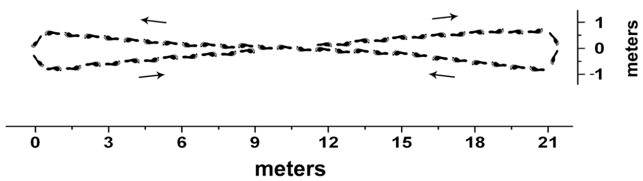
Signals were acquired by means of a multichannel recording system for statistical gait analysis (Step32, DemItalia, Italy). Step32 system allows the acquisition of up to 16 signals, performing a gait partition and myoelectric signal processing and analysis oriented to the identification of muscular activation/deactivation sequences. Step32 is able to acquire and analyse EMG signals belonging to hundreds of consecutive strides, with a statistical evaluation of the muscular activity during the entire walking trial. Each subject was instrumented with foot-switches, electro-goniometers and SEMG probes, cable-connected with the acquisition system. Three foot-switches (Step32, DemItalia, Italy) were applied beneath the heel, the first and the fifth metatarsal heads of each foot. An electro-goniometer (Step32, DemItalia, Italy, accuracy: 0.5 deg) was applied to the lateral side of each lower limb for measuring the knee joint angles in the sagittal plane. Single differential SEMG probes with fixed geometry constituted by Ag/Ag-Cl disks (manufacturer: DemItalia, size: 7 × 27 × 19 mm; electrode diameter: 4 mm; interelectrode distance: 8 mm, gain: 1000, high-pass filter: 10 Hz, input impedance > 1,5 GΩ, CMRR > 126 dB, input referred noise $\leq 1\ \mu V_{rms}$) were applied over the TA and GL of each lower limb following the SENIAM recommendations for electrode location and orientation over muscle with respect to tendons, motor point and fibre direction (Freriks et al., 1999). Participant setup is shown in Figure 1. Before positioning the probes, the skin was shaved, cleaned with abrasive paste and then wet with a soaked cloth. To assure proper electrode-skin contact, electrodes were dressed with highly-conductive gel. After positioning the sensors, subjects were instructed to walk barefoot over ground for around four minutes at their natural pace, following the path schematised in Figure 2 (Di Nardo and Fioretti, 2013). Natural pace was chosen because walking at a comfortable speed improves the repeatability of SEMG data, while variability increases when subjects are required to walk abnormally (Kadaba et al., 1989). The possibility of cross-talk was checked for by visual inspection of raw data. In order to avoid inter-operator variability, cross-talk checking was made by the same operator, expert in the field of EMG data acquisition and interpretation. Cross-talk was suspected when two muscles in the same limb section showed simultaneous activity with similar amplitude modulation.

Figure 1 Participant set-up. three foot-switches were applied beneath the heel, the first and the fifth metatarsal heads of each foot



Notes: An electro-goniometer was applied to the lateral side of each lower limb for measuring the knee joint angles in the sagittal plane. Two single differential SEMG probes with fixed geometry were applied over the TA and GL of each lower limb following the SENIAM recommendations

Figure 2 Schematic representation of the path walked by the recruited subjects during the experiment; subjects walked barefoot over the floor for four minutes at their natural pace



2.3 *Signal processing*

Foot-switch signals were converted to four levels. Corresponding to heel contact (H), flat foot contact (F), push off (P), swing (S), according with what has been reported in Agostini et al. (2014) and in order to maintain the accuracy of gait phases detection, avoiding an excessive granularity of the gait cycle (Taborri et al., 2016). During acceleration, deceleration, and changes in direction the strides are different from those of steady state walking. Therefore, the knee joint angles in the sagittal plane (low-pass filtered with cut-off frequency of 15 Hz) along with gait phase durations, were used by a multivariate statistical filter embedded in the Step32 system, to detect and discard outlier cycles, i.e., cycles with the proper sequence of gait phases (H-F-P-S) but with abnormal timing, like those relative to deceleration, reversing, and acceleration (Agostini and Knaflitz, 2012). SEMG signals were high-pass filtered (cut-off frequency of 20 Hz) and processed by a double-threshold statistical detector, embedded in the Step32 system, that provides the onset and offset time instants of muscle activity in a completely user-independent way (Bonato et al., 1998). This technique (Bonato et al., 1998) consists of selecting a first threshold ζ and observing m successive samples: if at least r_0 out of successive m samples are above the first threshold ζ, the presence of the signal is acknowledged. In this approach, the second threshold is represented by r_0. Thus, the behaviour of the double-threshold detector is fixed by three parameters: the first threshold ζ, the second threshold r_0, and the length of the observation window m. Their values are selected to jointly minimise the value of false-alarm probability and maximise probability of detection for each specific signal-to-noise ratio. The setting of the first threshold, ζ, is based on the assessment of the background noise level, as a necessary input parameter. Furthermore, the double-threshold detector requires to estimate the signal-to-noise ratio in order to fine tune the second threshold, r_0. The values of the background noise level and the signal-to-noise ratio, necessary to run double-threshold algorithm, is estimated for each signal by Step32 system, using the statistical approach proposed by Agostini and Knaflitz (2012). The length duration of the observation window, m, of 30 ms is considered a suitable value for the study of muscle activation in gait analysis (Bonato et al., 1998).

Considering the non-invasiveness of the surface electromyography technique and the experimental setup described earlier, subjects performed walking trials in a full-physiological way, allowing to refer the final outcomes to a real situation.

During gait, a muscle activates a number of times which is usually variable from cycle to cycle (Agostini and Knaflitz, 2012). Thus, muscle on/off instants should be averaged considering each single modality of activation by itself. With modality of activation we mean the number of times when muscle activates during a single gait cycle, i.e., n-activation modality consists of n activation intervals for the considered muscle, during a single gait cycle. In the present study, mean activation intervals (normalised with respect to the gait cycle) for each modality of activation were achieved by means of the Step32 system, according with the following steps. First, muscle activations relative to each gait cycle were identified. Then, for all the gait cycles corresponding to straight line walking, muscle activations were grouped according with the number of activations detected, i.e., relatively to the modalities of activations detected. Finally, the on/off time instants were averaged, for each specific modality of activation observed and relative standard deviation (SD) and standard error were computed. In the present study, only gait cycles consisting of the proper sequence of gait phases of (H-F-P-S) were considered.

2.4 *Statistics*

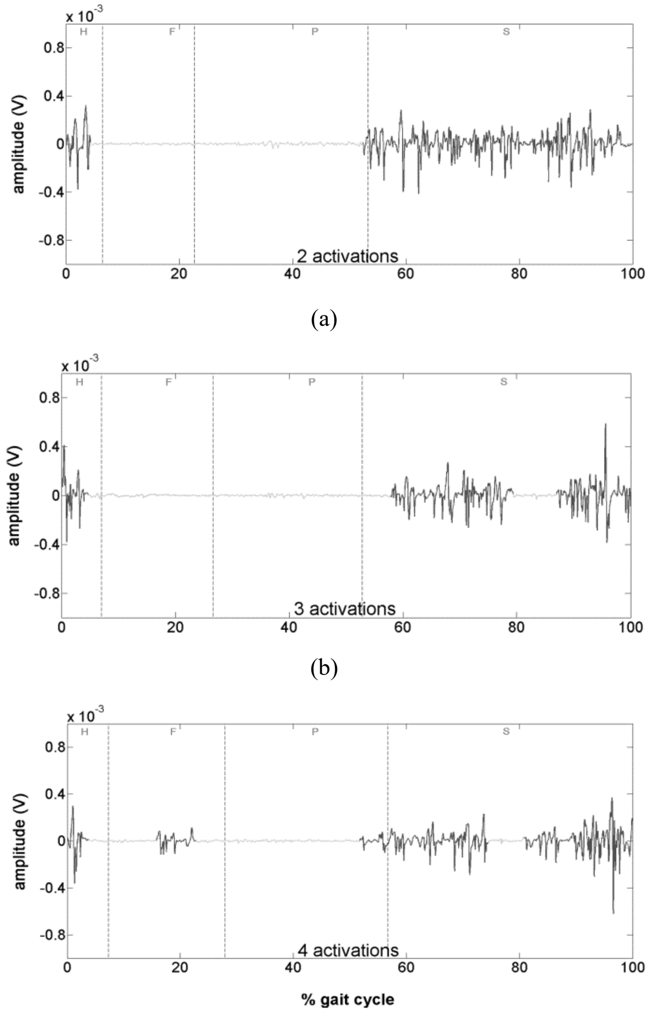
Data are reported as mean ±SD with data from right and left lower limb considered all together. The Lilliefors test (suitable for small samples) was used to evaluate the hypothesis that each data vector or parameter vector had a normal distribution with unspecified mean and variance (Lilliefors, 1967). Comparisons among normally distributed samples were performed with two-tailed, non-paired Student's t test while Mann-Whitney U-test was used to compare not-normally distributed samples. For normally-distributed samples, the analysis of variance (ANOVA) was used to compare different activation modalities within each group, whereas for not-normally distributed samples Kruskal-Wallis test was employed. ANOVA and Kruskal-Wallis were both followed by multiple comparison test, according with Tukey's procedure. Statistical significance was set at 5% level for every test used in the present study.

3 Results

Mean (±SD) characteristics of the gait cycle are the following. For the F-group: gait cadence = 58.4 ± 2.7 cycle/minute; gait speed = 1.16 ± 0.10 m/s; duration of gait cycle = 1.05 ± 0.05 s; length of single support phase (expressed in percentage of gait cycle) = 42.9% ± 2.7%, length of double support phase (expressed in percentage of gait cycle) = 14.1% ± 5.2%, length of stance phase (expressed in percentage of gait cycle) = 57.1% ± 2.7 %, length of stance phase (expressed in percentage of gait cycle) = 42.9% ± 2.8%. For the M-group: gait cadence = 53.5 ± 2.7 cycle/minute; gait speed = 1.19 ± 0. 09 m/s; duration of gait cycle = 1.13 ± 0.07 s; length of single support phase (expressed in percentage of gait cycle) = 43.8% ± 2.2%, length of double support phase (expressed in percentage of gait cycle) = 12.4% ± 2.8%, length of stance phase (expressed in percentage of gait cycle) = 56.2% ± 2.2%, length of stance phase (expressed in percentage of gait cycle) = 43.8% ± 2.2%. No significant differences ($p >$ 0.05) between F and M groups were detected in all variables, except for cadence that was significantly higher ($p < 0.05$) in F-group.

The present study compared M and F groups in terms of the frequency each modality of muscle activation occurs with, quantified by the number of strides (%), over the total subjects, where the muscle is recruited with the specific modality of activation. To clarify the meaning of modality of activation, an example of SEMG signals from GL and TA muscles of a single subject have been reported in Figures 3 and 4, respectively.

Figure 3 Example of SEMG signals from GL acquired in the same subject, from different strides of the same walking trial



(a)

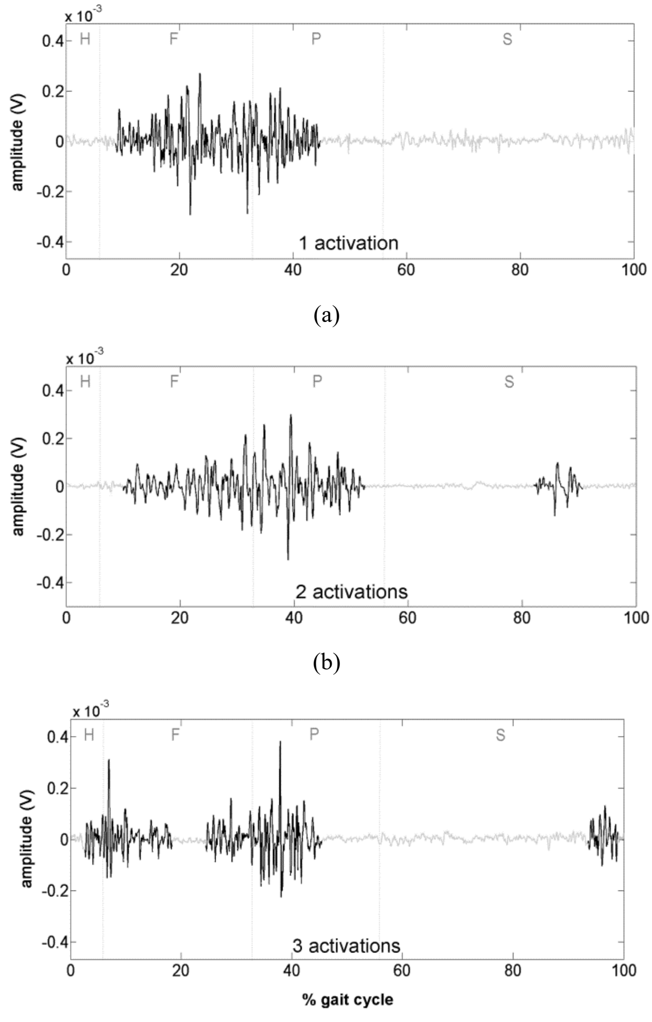
(b)

(c)

Notes: In panel A, GL shows one activation (1-activation modality), in panel B, GL shows two activations (2-activation modality) and in panel C, GL shows three activations (3-activation modality). Heel contact (H), flat foot contact (F), push off (P) and swing (S) phases are delimited by dashed light-gray vertical lines.

In the matter of GL, the most recurrent modality of activation (Figure 5) consists of two activations (2-activation modality) for the F-group (observed in 39.3% ± 9.8% of the total strides) and of one single activation (1-activation modality) for the M-group (observed in 48.3% ± 16.8% of the strides). The second most recurrent modality of activation consists of three activations (3-activation modality) for the F-group (observed in 36.4% ± 9.4% of the total strides) and of two activations (2-activation modality) for the M-group (observed in 34.1% ± 9.7% of the strides). Finally, the less recurrent modality of activation consists of one activation (1-activation modality) for the F-group (observed in 10.1% ± 6.2% of the total strides) and of three activations (3-activation modality) for the M-group (observed in 13.35 ± 6.1% of the strides). Compared with F-group, M-group presented, on average, a significantly higher ($p < 0.001$) frequency of occurrence in the 1-activation modality and a significantly lower frequency of occurrence in the 3-activation modality ($p < 0.001$). No significant differences were detected between the two groups in the 2-activation modality (Figure 5).

Figure 4 Example of SEMG signals from TA acquired in the same subject, from different strides of the same walking trial



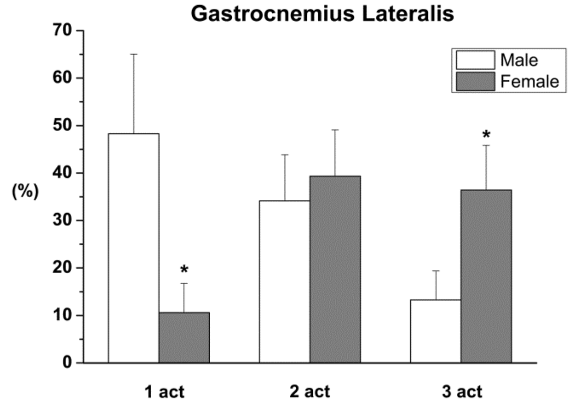
(a)

(b)

(c)

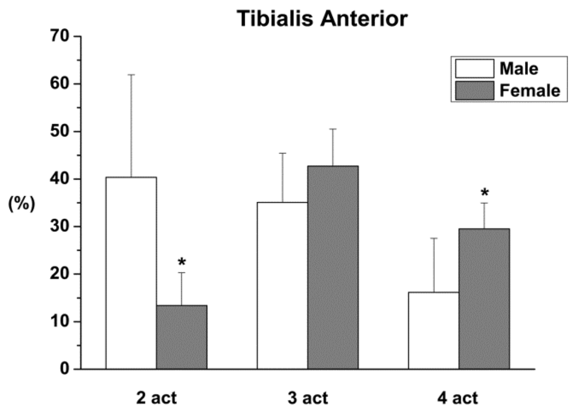
Notes: In panel A, TA shows two activations (2-activation modality), in panel B, TA shows three activations (3-activation modality) and in panel C, TA shows four activations (4-activation modality). Heel contact (H), flat foot contact (F), push off (P) and swing (S) phases are delimited by dashed light-gray vertical lines.

Figure 5 Averaged (+SD) frequency of occurrence of the three main modalities of activation detected during walking trial for GL



Notes: Data are expressed in percentage of total strides. Grey bars represent the frequency of muscle occurrence in the F-group and the white bars represent the frequency of muscle occurrence in the M-group. *Indicates that differences between F and M groups are statistically significant.

Figure 6 Averaged (+SD) frequency of occurrence of the three main modalities of activation detected during walking trial for TA



Notes: Data are expressed in percentage of total strides. Grey bars represent the frequency of muscle occurrence in the F-group and the white bars represent the frequency of muscle occurrence in the M-group. *Indicates that differences between F and M groups are statistically significant.

In the matter of TA, the most recurrent modality of activation (Figure 6) consists of three activations (3-activation modality) for the F-group (observed in 42.7% ± 7.8% of the total strides) and of two activations (2-activation modality) for the M-group (observed in 40.4% ± 21.5% of the strides). The second most recurrent modality of activation consists of four activations (4-activation modality) for the F-group (observed in 29.5% ± 5.4% of the total strides) and of three activations (3-activation modality) for the M-group (observed in 35.1% ± 10.4% of the strides). Finally, the less recurrent modality of activation consists of two activations (2-activation modality) for the F-group (observed in 13.4% ± 6.9% of the total strides) and of four activations (4-activation modality) for the M-group (observed in 16.2% ± 11.3% of the strides). Compared with F-group, M-group showed, on average, a significantly higher ($p < 0.01$) frequency of occurrence in the 2-activation modality and a significantly lower frequency of occurrence in the 4-activation modality ($p < 0.01$). No significant differences were detected between the two groups in the 3-activation modality (Figure 6). Since the strides where GL showed 1, 2 and 3-activation modalities and TA showed 2, 3 and 4-activation modalities cover the 90 % of total strides, we limited our analysis to these three main modalities of activation.

The mean results are reported with data from right and left lower limb considered all together.

4 Discussions

The aim of the present study was to evaluate possible differences between males and females in the EMG activity of TA and GL, during gait. Compared to females, males showed a significant lower mean cadence during the walking trial; despite these differences, females and males are keeping the same comfortable speed and cycle duration (see Section 3). In percentage, also the stance phase, the swing phase, and the period of single support vs. double support remained unaltered between the two populations. Thus, the full picture of gait temporal parameter suggests no significant differences between male and female way of walking. These results agree with what was reported in previous studies (Kerrigan et al., 1998; Oberg et al., 1993).

The present statistical analysis put into evidence that both GL and TA show different activation modalities, i.e., different number of activations, in different strides of the same walking trial. This has been observed for both female and male populations. Variability in the modalities of ankle muscles activation was reported also in previous works in healthy adults (Di Nardo et al., 2013, 2014, Di Nardo and Fioretti, 2014) and in school-age children (Agostini et al., 2010).

The first relevant difference detected in the SEMG signal between F and M groups lies in the identification of the most recurrent modality of activation for both GL and TA (Figures 5 and 6); females show a preference towards more complex modalities (2 and 3-activation modality for GL and TA, respectively), compared with males (1 and 2-activation modality for GL and TA, respectively). In the identification of the less recurrent modality of activation, a similar behaviour has been observed: in females, the less frequent modality of activation coincides with the simplest one, for both GL (1-activation modality) and TA (2-activation modality); in males, the less frequent modality of activation coincides with the most elaborate one, for both GL (3-activation modality) and TA (4-activation modality). The female preference for walking with more complex modalities of activation, with respect to male, is supported by the following further considerations. In the M-group, the simplest activation modalities are also the most recurrent ones, for both GL (1-activation modality) and TA (

2-activation modality); moreover, it has been observed a gradual decrease of the frequency of occurrence with the increase of the complexity in the modalities of activation, for both GL and TA (white bars in Figures 5 and 6). In the F-group, the simplest activation modality occurs in a low percentage of strides (around 10%, for both GL and TA); moreover, both 2 and 3-activation modalities for GL are more recurrent than the 1-activation modality (the simplest one) and both 3 and 4-activation modalities for TA are more recurrent than the 2-activation modality (the simplest one). Also the direct comparison between the two groups supports the hypothesis of a preference of subjects from F-group for walking with more complex modalities of activation, with respect to M-group (Figures 5 and 6): the F-group, compared with M-group, shows a significantly higher frequency of occurrence in the modalities with an elevated number of activations (three, activations for GL and four activations for TA), and a significantly lower mean value of the occurrence frequency in the modalities with a low number of activations (one activation for GL and two activations for TA).

Thus, the concomitant occurrence of all these findings indicates a propensity of the females for adopting the modalities of activation with higher number of activation intervals, compared to the males. This suggests a more complex recruitment of TA and GL for females, during normal walking. Despite gender-related differences have been already reported in some motor tasks, such as landing (Decker et al., 2003; Gehring et al., 2009) and running (Ferber et al., 2003), to authors knowledge this study is the first in proposing the occurrence frequency as a suitable parameter which can mirror the role of gender in ankle-muscles myoelectric activity during a day-life task as the walking. The importance of these findings consists in demonstrating the necessity of a separate approach for males and females, in the utilisation of SEMG signals into gait analysis and for clinical and research studies. The importance of a separate approach increases when SEMG signals are provided as main input information to the controller of robotic systems, such as exoskeleton robot and powered orthosis. Moreover, the present findings can result particularly useful in clinical contexts, where EMG-driven devices are often employed for rehabilitation therapies from spinal cord injury (Del-Ama et al., 2012), stroke (Song et al., 2008), tremor (Rocon et al., 2007) and to regain the dexterity of upper and lower limb joints (Ho et al., 2011). Such devices are also employed for treatment of healthy subjects (Rosen et al., 2007). Telerobotics and computer vision application of these findings could be also considered (Avgousti et al., 2016).

Despite the accuracy of the methodology and the reliability of the results achieved, a limitation of the study can be found in the limited sample of the recruited subjects, in particular when the outcomes of the statistical analysis are evaluated.

5 Conclusions

The statistical analysis performed in the present study showed clear gender-related differences in the myoelectric activity of TA and GL, during gait at comfortable speed and cadence, in terms of their frequency of occurrence. The concurrence of many factors, such as a higher frequency of occurrence in the modalities with an elevated number of activations and a concomitant lower mean occurrence frequency in the modalities with a low number of activations in females, indicates a propensity of the female for a more complex recruitment of the muscles during gait.

This information suggests considering a separate approach for males and females, in providing EMG signals as main input information to the controller of exoskeleton robot and powered orthosis.

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