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SVM classification of locomotion modes using surface electromyography for applications in rehabilitation robotics

E. Ceseracciu, M. Reggiani, Z. Sawacha, M. Sartori, F. Spolaor, C. Cobelli, E. Pagello

Abstract— **The next generation of tools for rehabilitation robotics requires advanced human-robot interfaces able to activate the device as soon as patient's motion intention is raised. This paper investigated the suitability of Support Vector Machine (SVM) classifiers for identification of locomotion intentions from surface electromyography (sEMG) data. A phase-dependent approach, based on foot contact and foot push off events, was employed in order to contextualize muscle activation signals. Good accuracy is demonstrated on experimental data from three healthy subjects. Classification has also been tested for different subsets of EMG features and muscles, aiming to identify a minimal setup required for the control of an EMG-based exoskeleton for rehabilitation purposes.**

I. INTRODUCTION

The increasing number of disabilities related to an aging society requires efficient solutions for rehabilitation and assistance. Indeed, current rehabilitation facilities are still traditional and quite expensive as they require the continuous presence of a therapist. Introducing advanced solutions, such as powered orthoses, could reduce the hospitalization and the number of required therapists thus lowering the costs related to personal health service. Although great progress has been made in the century long effort to design and implement robotic exoskeletons and powered orthoses, many design challenges still remain [1]. Remarkably, there are many factors that continue to limit the performance of exoskeletons and orthoses. For example, neuromechanical models [2], [3] that capture the major features of human walking could improve understanding of musculoskeletal morphology and neural control and lead to analogous improvements in the design of economical, stable and low-mass exoskeletons for human walking augmentation [1]. Another factor limiting current exoskeletons and orthoses is the lack of direct information exchange between the human wearer's nervous system and the wearable device. Peripheral sensors placed inside muscles to measure the electromyographic signal, or sensors placed centrally into the motor cortex, may be used to assess motor intent by future exoskeletal control systems [1].

In our research, we decided to focus our efforts on the development of supporting devices for lower limbs, as restoring movement and functional abilities has a great impact on quality of life, simplifying the creation of social interaction. Additionally, there is a lack of research on such machines compared with the advancements on upper extremity exoskeletons. While the latter have been studied for more than ten years, only recently particular attention has been put on lower extremity exoskeletons and human gait support despite the potentially large number of consumers for such machines [4], [5], [6], [7], [8]. Most of current computerized assisting robotic systems and rehabilitation devices for lower limbs only allow the user to change the movement mode manually [9]. Such procedures are relatively complicated, therefore more advanced interfaces are required, able to seamlessly activate the devices as soon as patients' motion intentions are raised. With respect to previous researches, we plan to develop lower limb powered orthoses with similar electric linear actuation systems that allow knee flexion-extension and hip and ankle joint movements, but with a more sophisticated sensor system to capture a broader set of parameters and provide proper input for the orthosis control unit. Electromyography (EMG) signals registered from muscles during their activation are one of the major sources of information about neural control. During the execution of the movement, these signals can be captured, interpreted and used as input for the control algorithms. The main problem with EMG signals is that they are not stationary, therefore their use to recognize patient's task intentions can result in low accuracy when whole locomotion cycles are taken into consideration.

A few recent works have shown that the difficulties in classifying different tasks could be partially overcome reducing the duration of the time windows where task characterizing features are captured [9], [10].

The objective of this paper is to show the feasibility of a robust lower limb task classifier exploiting EMG. We investigate the suitability of Support Vector Machine (SVM) [11] to recognize locomotion modes when features are computed in a short time window. So far, the adoption of SVM in classification of myoelectric signals is still limited and only applied to upper limb [12]. The aim of the final classifier is to learn the difference among the features collected during different locomotion modes. As shown in the experimental results, current implementation of the classifier allows to predict the unlabeled new executions from the signals captured from leg muscles with a high level of accuracy.

The paper is organized as follows. Section II provides a high-level description of the methodology used for data acquisition and evaluation, together with a soft introduction to Support Vector Machine. Section III presents the experimental results and a brief discussion on the benefits achievable with the proposed procedure. Finally, Section IV summarizes

E. Ceseracciu, Z. Sawacha, F. Spolaor, C. Cobelli are with the Department of Information Engineering, University of Padova. M. Sartori, E. Pagello are with the Department of Information Engineering, University of Padova and with the Institute of Biomedical Engineering - National Research Council, Padova, Italy. M. Reggiani is with the Department of Technique and Management, University of Padova, Vicenza, Italy monica.reggiani@unipd.it.

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the research and introduces further developments.

II. METHODOLOGY

A. Subjects

Three healthy subjects were consecutively recruited for this study, 2 female and 1 male, with a mean age of 29±8.9 years and a mean body mass index (BMI) of 21.9±0.2 $\frac{kg}{m^2}$.

B. Experimental Set up

Each subject's right leg muscular activity was monitored through a sixteen channels surface electromyography (sEMG) system (Pocket EMG, BTS Spa, frequency 1KHz). sEMG signals were detected from the following muscles: *gluteus maximus (GLMA), gluteus medius (GLME), sartorius (SAR), rectus femoris (RF), vastus lateralis (VAL), vastus medialis (VAM), gracilis (GR), biceps femoris caput longus (BFCL), semitendinosus (ST), tibialis anterior (TA), peroneus longus (PEL), gastrocnemius lateral head (GAL), gastrocnemius medial head (GAM), soleus (SOL) and extensor digitorum brevis (EXD)*. Fifteen bipolar and 1 monopolar signals were acquired using 31 monopolar pre-gelled electrodes (ARBOsensor Ag/AgCl, size 24 mm, and FIAB PG10S, Silver Silver-Chloride 8Ag/AgCl, size 26 mm, interelectrode distance 10 mm). For each muscle, the center of the electrode grid was placed in the location suggested by Blumenstein and Basmanjian [13]. Before electrode placement, the skin was shaved and abraded with abrasive paste (Meditec-Every, Parma, Italy). A ground electrode was also placed on the bone of the knee of the tested leg. Three foot switches were attached under the monitored foot in corrispondence of the first and fifth metatarsal head, and the calcaneus. A six cameras (120-160Hz) stereophotogrammetric system (BTS SpA, Padova) was used to collect lower limb kinematics, synchronized with the sEMG system. Five passive markers were applied in correspondence of the great throcanter, lateral femoral epicondyle, lateral malleolus, medial heel, head of fifth metatarsal. Two webcams (Microsoft LifeCam VX-7000) were used to record videos of the testing session. Subjects wore shorts that did not impede hip and knee motion. After attachment of the foot switches, subjects were allowed to walk until they were comfortable on a surface covered by linoleum. They walked bare foot at self selected pace in the gait lab 8m long and 3m wide. Each subject performed the following motion modes: *level walking, stepping over an obstacle, turning right, ascending stairs, descending stairs, standing still*. During the static acquisition subjects were asked to stand for 60 seconds in an upright position, with their feet 30°apart and their arms along the body, and to look at a small achromatic circular target placed about 1 meter from the eyes [14], [15], [16]. Stepping over an obstacle was performed asking the subject to step over a wooden block of 14.5 cm hight, 40 cm width and 28.5 cm depth, while walking. In this context the non-testing side passed over the obstacle first, followed by the instrumented leg. A two-step staircase 16 cm high, 80 cm wide, and 28 cm deep was used for the stair ascending and descending test. The turning right was acquired asking the subject to perform a 90° turn while walking, pivoting on their own controlateral leg. Each subject perfomed the 6 motion modes randomly during each trial within the same experimental session. At least 12 complete stride cycles of each task were acquired.

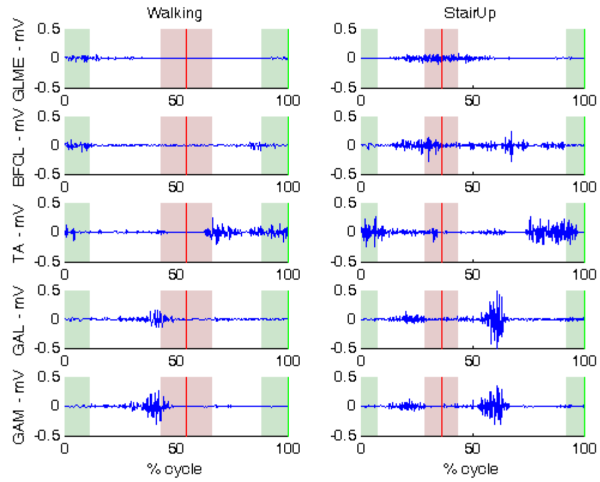

Fig. 1. Example of filtered sEMG signals for two types of locomotion modes (left: level ground walking; right: ascending stairs). A contact-to-contact cycle is reported. FootContact and footOff events are shown (green and red vertical lines, respectively). Analysis windows that are taken into consideration are also highlighted: from left to right, the first green area corresponds to postContact phase, then preOff and postOff (red areas) occur respectively before and after footOff, finally preContact is shown as occurring before the following footContact event (last green area).

C. Signal Analysis

The first and the last strides were excluded from each trial due to walking initiation and termination. Each subject's gait speed was checked by means of the foot switches data in order to verify whether it fell within the normal range, since muscle activation is related to gait velocity [17]. Timings of footContact and footOff events were identified by means of basographic and motion analysis data. FootContact is characterized by the activation of any of the three foot switch signals; similarly, footOff is recognized by the deactivation of all signals. Analysis windows were identified as occurring immediately before or after these discrete events. Four phases are therefore taken into consideration, namely preContact, postContact, preOff and postOff (figure 1). Window length has been set to 150 ms following recommendations in literature: EMG signals can be considered quasi-stationary within 200 ms intervals, while they are not sufficiently informative when analysis windows shorter than 50 ms are used [9]. Features were extracted from filtered EMG signals (3rd-order zero-lag Butterworth filter, passband 10-450 Hz; Matlab, Mathworks Inc.) in every analysis window, in order to provide a concise characterization suitable for classification. Both time-domain values, i.e. mean absolute value (MAV), number of zero-crossings (ZC), waveform length (WFL), number of slope sign changes (SSC), root mean square (RMS) [10], and 3rd-order auto-regression coefficients (AR1, AR2, AR3) [9] were considered.

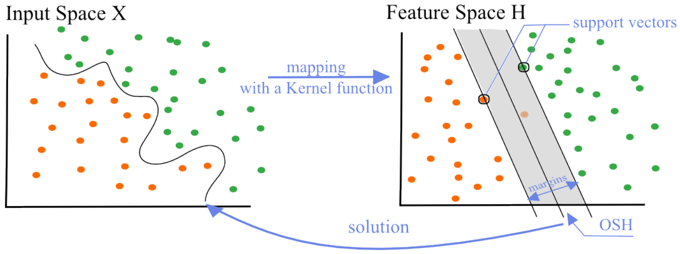

Fig. 2. Two classes are not linearly separable in the input space X. A kernel function is used to map X in a feature space H where the two classes become linearly separable. The hyperplane built by SVM algorithm in H corresponds to a non-linear solution in the input space X.

D. Support Vector Machine

Support vector machine (SVM) algorithm is a well established technique to learn how to classify new data starting from a collection of classified events. In this research, the classified events are feature vectors collected in the same phase during different locomotion modes. SVM learns the differences between them and predicts the corresponding mode for an unlabeled vector. Training and subsequent testing are performed independently for each subject.

This section does not aim to cover the strong SVM theoretical foundations [18] nor the large number of its successful applications [11]. Instead, it will briefly sketch the ideas and motivations behind SVM, explaining its four basic concepts: (i) the separating hyperplane, (ii) the kernel function, (iii) the optimal separating hyperplane, and (iv) the soft margin. Later, we will introduce its extension to multiclass classification.

The main objective of a SVM algorithm is to identify a line, or *hyperplane* in a n-dimensional space H (figure 2), *separating* a set of input points, each one known to belong to either one of two different classes. If the algorithm is successful in finding an hyperplane that reduces the probability of misclassifying future data, the new sample is easily classified based on what side of the hyperplane it lies on. Often it is not possible to linearly separate the data in the original space X, requiring SVM to map the input data in a higher dimensional space H, through a *kernel function*. The objective is to find the kernel function that allows the data to be linearly separated. While it has been proved that this is always possible, the final dimension of the space H could be intractable. In the higher dimensional space H, it is usually possible to identify several linear classifiers that separate the data. Intuitively, the *optimal separating hyperplane* (OSH) that maximizes the prediction capability of new samples is the one that lies in the middle. Formally, the OSH is the hyperplane that maximizes the margin that separates the distance between the hyperplane and the nearest data points of each class. The points closest to OSH are called *support vectors*.

Data can often contain errors. To deal with the noise in the training data, the original OSH algorithm would overfit the data: a solution is indeed found, but at the price of a useless increment in the dimension of the feature space H. To tolerate training errors, the SVM algorithm is modified introducing the concept of *soft margin*. Intuitively, this allows to tolerate a few outliers on the wrong side of the hyperplane. Deciding the number of input violations and the size of the margin requires a process of parameter tuning for the problem at hand.

Multiclass SVM The generalization to multiclass classification can be achieved with different methods. Two basic strategies are the one-against-all and the one-against-one. In the one-against-all, the system is trained with each class classified against the samples of all the other classes. A better solution, reducing ambiguous classification [19] is the one-against-one strategy, where classes are classified in pair. Given m classes, $m(m-1)$ binary classifiers are built and trained to discriminate between a pair of classes. Then we construct a bottom-up binary tree for classification. At the first level $m/2$ classes are selected by $m/2$ classifiers, each one trained with data from a pair of different classes. The $m/2$ "winners" go to the next (upper) level, where $m/4$ classifiers, trained with pairs of the winner classes, select the "winners" that go to the next step. The final class, reaching the top of the binary tree, is the class predicted by the multiclass SVM.

E. Validation

Estimation of classification error is performed by means of leave-one-out cross-validation (LOOCV). This procedure is used to assess how classification results generalize to a dataset that has not been involved in the training process, even when a proper validation set is not available. Every sample in the dataset is therefore used to test the multiclass SVM trained with all the other samples. This validation technique is widely used in data-poor situations, where a small number of samples is available for each class under investigation. Performance can therefore be quantified in terms of overall classification error, i.e. the ratio between the number of samples that are not classified correctly and the size of the whole dataset. A deeper insight into the behavior of the classifer can be obtained summarizing LOOCV results in a confusion matrix. This is a square matrix of size m (number of classes). Element c_{ij} represents the percentage of samples belonging to class j that are classified as belonging to class i. If no errors occur, the confusion matrix is an identity matrix. Analysis of this matrix allows to identify the pairs of classes that are not clearly separated by the OSH.

III. EXPERIMENTAL RESULTS

The experiments presented in this section are implemented using libSVM, a freely available implementation of the SVM classifier [20]. This library is designed to help users from other fields to easily use SVM and it provides a set of tools to optimize SVM parameters. The whole set of experimental results has been obtained using the RBF kernel function. While other kernels are available, we have not compared their performances, as this was not part of the objectives of this work. Instead, we have chosen a kernel that has already demonstrated good accuracy in the classification of upper

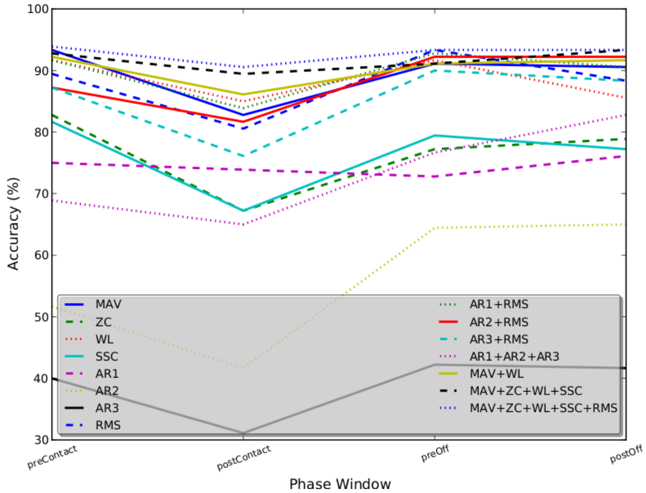

Fig. 3. Classification accuracy for different sets of feature types. For each phase, results were averaged over all the subjects and locomotion modes. Time-domain features outperform autoregressive coefficients.

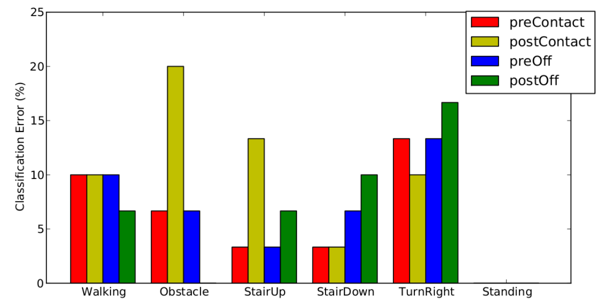

Fig. 4. Average classification errors for each locomotion mode in the four phases. Accuracy is phase dependant and locomotion modes are affected differently. Standing data is never misclassified.

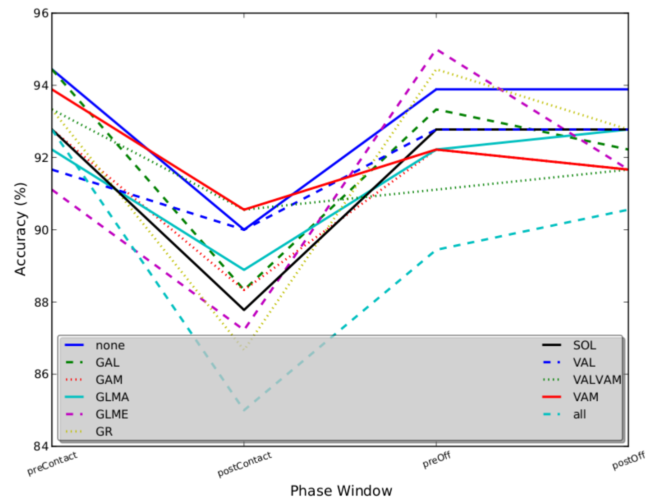

Fig. 5. SVM classification accuracy for reduced sets of muscles, and optimal set of feature types. Muscles have been removed one at a time from the set; the legend shows the corresponding acronym. Accuracy for the proposed minimal set (GLME, SAR, RF, BFCL, ST, TA, PEL, GAM, EXD) is also shown.

limb motions [12]. Additionally, the RBF kernel is usually a reasonable first choice as it can handle the nonlinear relation between class labels and attributes [21].

A. Feature Selection

Classification accuracy for data samples composed of different subsets of EMG features from all muscles has been analyzed. Results, shown in figure 3, confirm that time-domain features outperform autoregressive coefficients, as reported in [9]. This is particularly evident from the performances obtained when each type of feature was employed separately. Since all these time-domain features can be calculated in real-time with minimum computational cost, they have been used to generate data samples in all subsequent analyses.

B. Phase dependent accuracy

Phase dependency of classification accuracy has also been demonstrated. Best-case average accuracy (time-domain features, all muscles) ranges from 90% (postContact) to 95% (postOff), as figure 3 illustrates. In addition, we show that the phase influences accuracy in a different way for each locomotion mode (figure 4). *Stepping over an obstacle*, for example, is recognized successfully in postOff phase, while in postContact it is easily classified as *walking*, as clarified by figure 6. *Walking* instead has more consistent errors along the different phases.

C. Muscle selection

Since the number and position of electrodes to be placed on a subject strongly affect the design of the exoskeleton and its usability, particular effort has been made to reduce the set of muscles that are needed to achieve acceptable classification results. Classification accuracy has therefore been estimated on data samples obtained excluding one or more muscles from the feature extraction process. Results of this analysis are shown in figure 5. At first muscles have been removed one at a time, on basis of biomechanics considerations: muscles whose biomechanic function is also carried out by some others have been considered in this phase. For example, vasti (VAL and VAM) have the same role as knee extensors as RF, which also acts as hip flexor; glutei (GLMA and GLME) are both hip extensors; gastrocnemii (GAL and GAM) are knee flexors and are involved in plantarflexion of the foot, as well as soleus (SOL) [17]. Following this preliminary analysis, classification performances have been tested excluding a full set of muscles, namely GLME, VAL, GR, GAL, SOL. Confusion matrices averaged over the three subjects are shown for the complete set of muscles (figure 6) and this reduced set (figure 7) for all four phases.

D. Discussion

In the present contribution we studied the classification performance of SVM method on multi-channel sEMG data collected from healthy subjects during different lower extremity motion movements.

Although only a small sample of subjects was considered

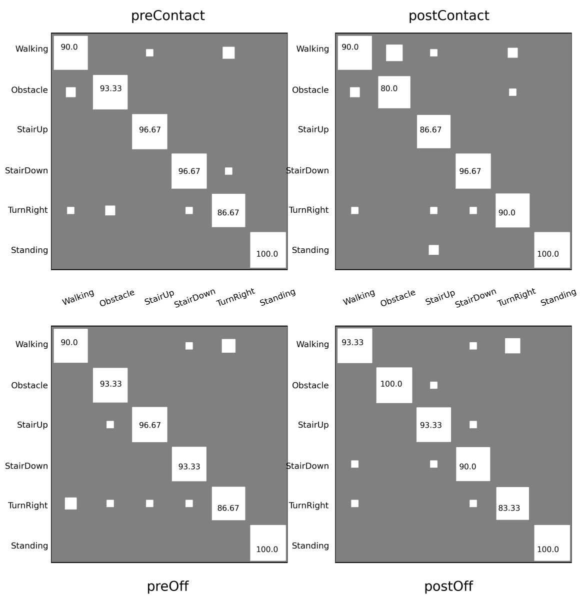

Fig. 6. Hinton diagram of the average confusion matrix that represents classification accuracy on the optimal set of features extracted from all muscles. The size of the squares is proportional to matrix values; full size corresponds to 100% accuracy. Classification errors mainly occur for *turn right* class.

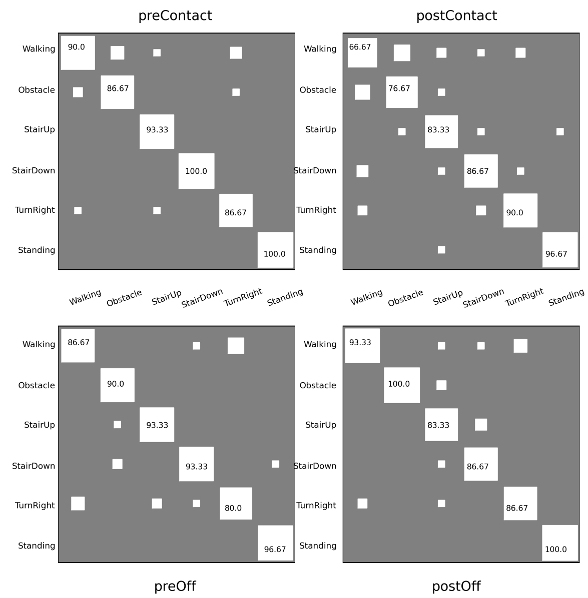

Fig. 7. Hinton diagram of the average confusion matrix that represents classification accuracy on the optimal set of features extracted from the proposed minimal set of muscles (GLME, SAR, RF, BFCL, ST, TA PEL, GAM, EXD).

in order to test the methodology's feasability, the average classification accuracy obtained on the whole set of movements is encouraging and stimulates further research. The misclassification errors are, indeed, concentrated on tasks which are quite similar and, therefore, corresponding sEMG features may become difficult to distinguish. When the obstacles are narrow and low, or the turning is not abrupt, it is likely that there will be difficulties for their discrimination with respect to level-ground walking. We expect that this should not be a problem as the support provided by the powered orthoses should also have similar behavior in the confused motion modes.

Since EMG signals can be considered quasi-cyclic during a locomotion mode, phase dependency of classification was analyzed. General footContact and footOff events were defined, which allows classification also of those motion modes performed without the heel or the toes necessarily touching the ground. This has been motivated by the observation that several pathologies, caused by injury to supraspinal centers, lead to motor impairment related to muscle atrophy; this prevents the foot from touching the ground with the normal locomotion mode, which entails heel contact and hallux push off [17], [22]. These same pathologies will likely benefit from adoption of exoskeleton-driven rehabilitation therapies [1]. The definition of phases here adopted should be considered an extension of the work of Huang et al. [9] which considered the phases prior and post to heel contact, and prior and post to toe off.

Another important contribution was demonstrating that when SVM classification is applied reducing the number of muscles according to their specific biomechanics function, it still can detect quite precisely the different motion modes. The rationale of this type of analysis is to relax the design requirements of exoskeletons. In the following we will give biomechanical details motivating the choices we made regarding muscle selection. The original sEMG protocol was defined considering the physiology governing muscle recruitment during the analyzed motion modes. Not only the type of muscles but also their activation timing during the execution of motor tasks were taken into account. GLMA, GLME, and BFCL regulate hip extension, which is particularly important during pre- and postContact phases. GLMA and BFCL, together with GR, are also hip adductors, therefore are activated in pre- and postOff phases. GLME instead acts as hip abductor during Contact phase. Hip flexion is regulated by RF, GR and SAR during postContact, preOff and postOff phases. As for knee motion, it is mainly regulated by quadriceps' VAL, VAM, RF and by GLMA (extension, pre and postContact), and by GAL, GAM, SAR, BFCL, GR (flexion, postContact, pre and postOff). Finally, the ankle joint motion can be described efficiently by means of its dorsal (TA, EXD) and plantarflexors (GAL, GAM, SOL, PEL). The latter are generally active during postContact, while activity of the formers can be registered during all four phases, as they often partecipate in the control of plantarflexion velocity reduction during Contact [17], [22].

Some muscles are therefore responsible for motion of more than one joint, while others regulate a specific joint function completely overlapping the action of other muscles.

The influence of single muscles' EMG signal on the classifier has been verified by testing its performance while excluding one muscle at the time. Analyzing these results within the biomechanical context that has been described, a full set of muscles was excluded, namely GLMA, VAL, GR, GAL, SOL. This version may be considered as a good trade-off between reduced instrumental set up and classification performance.

Further experiments need to be conducted in order to verify whether these findings generalize to amputees and hemiplegic patients, who present varying muscle coordination and motor control strategies [23].

IV. CONCLUSIONS

An effective powered orthosis requires the development of innovative neuromuscular human-machine interfaces. The robotic device worn by the patient should understand the desired movement and facilitate its execution providing active support to the subject. The interface should be implemented as an hybrid framework integrating different technologies to derive parameters that could not be obtained using a single approach and overcoming limitations of the single approach. A useful component of such a framework is a classifier, able to discriminate among a set of predefined locomotion modes with high classification performance. In this paper we have developed and evaluated a classifier based on support vector machine. Experimental results show that SVM provides good accuracy when a time dependent multifeature set is used. Additionally, the misclassification errors are mostly on pair of tasks with high similarity, such as walking and stepping over an obstacle, which should also require similar active support. Finally, the results on the selection of important muscles demonstrates that it is possible to reduce the number of sEMG signals without significantly affecting the classifier accuracy. This allows to reduce the number of electrodes to place on the leg, thus improving the usability of a powered orthosis. In the future, we are planning to investigate the advantages that could be gained through the combination of classification results obtained in sequential phases. Additionally, we will consider alternative classifiers, such as linear discriminant analysis and neural networks, to investigate which approach gives better classification performance while retaining enough efficiency to be used at run-time.

Although results achieved in our work are promising, the classifier still could not be used stand alone for the control of a device. We are currently working on a neuromusculoskeletal (NMS) model of the human lower limb [2], [3] to compute muscle forces. We expect that features based on forces and joint torques, which are more representative of the actual movement than sEMG signals, will enhance the classifier performance. Additionally, both the classifier and the NMS model will be integrated in a common framework to allow the real-time estimation of muscle activity, joint torques, and human motor intention.

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