Statistical Gait Analysis Based on Surface Electromyography.

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Statistical Gait Analysis Based on Surface Electromyography

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Abstract

To help neurologists, physicians, and physical therapists in the management of patients with altered locomotion AQ1 patterns, it is of the uttermost importance relying on accurate measurements of gait. Gait analysis becomes even more informative if the electrical activity of muscles is recorded, non-invasively, during the dynamic task of walking, through surface electromyography (sEMG) probes. However, sEMG AQ2 signals must be processed through advanced techniques to obtain reliable results, easily interpretable by healthcare practitioners. Indeed, the study of how muscles are activated during natural walking (in unconstrained environments) is complex for several reasons, including a high stride-to-stride variability, even more pronounced in pathological subjects. On the other hand, it is crucial to provide clinicians with aggregated information relying on validated parameters and easily usable representations that can be effectively included in clinical reports. This chapter is aimed at introducing: (1) Statistical Gait Analysis (SGA) to automatically analyze hundreds of gait cycles collected during a physiological or pathological walk lasting several minutes, (2) the extraction of principal and secondary muscle activations to obtain consistent clinical indexes, (3) the extraction of "muscle synergies" to quantitatively study motor control strategies. Each of these techniques are based on state-of-the-art processing algorithms of the sEMG signal. A brief review of the recent literature published in this field will be presented and discussed.

Keywords

EMG
Gait analysis
Locomotion

Muscle activation patterns
Muscle synergies

1. Introduction

The objective and quantitative study of human movement can be fundamental to support clinicians in the diagnosis and evaluation of rehabilitation outcomes of neurologic and orthopedic patients showing altered gait motor patterns and postural balance instabilities. Instrumented gait analysis provides comprehensive data on normal and pathological gait, producing information about spatio-temporal parameters (cadence, step length and duration, percentage of single- and double-support), and joint kinematics (angle of flexion–extension of ankle, knee, and hip) (Perry 1992). In addition, dynamic electromyography (EMG) allows for obtaining the action of muscles and their timing, contributing to outline the patient's walking pattern and an empirical basis for identifying the functional cause of a gait abnormality (Frigo and Crenna 2009; Cimolin and Galli 2014). Similarly, instrumented posturographic analysis provides objective data on the postural sway in upright stance, through the study of the Center-Of-Pressure (COP) signal (Agostini et al. 2011, 2013, 2016; Sbrollini et al. 2020).

In the past, the gold standard to perform gait analysis were stereophotogrammetric systems, i.e., 3D optical motion-capture systems. However, these systems are expensive, require a dedicated gait analysis laboratory and technical personnel, their sample volume is intrinsically limited to a few cube-meters, and they are complex to use, necessitating highly trained experts (typically biomedical engineers) to manage the system calibration and acquisition procedures. Hence, they proved to be unsuitable for clinical gait analysis. Force platforms were frequently used in conjunction to stereophotogrammetric systems to detect gait events, or as a standalone device to carry out posturographic analysis.

Systems based on Inertial Measurement Units (IMUs), integrating accelerometers, gyroscopes, and magnetometers into wearable sensors, are de facto completely replacing stereophotogrammetric systems and force platforms, offering valid low-cost alternatives to perform motion capture (MOCAP) (Agostini et al. 2015a; De Leonardis et al. 2018; Panero et al. 2018). Recently, this has caused considerable interest within the scientific community in the attempt to validate wearable systems in the clinical analysis of gait (Tao et al. 2012; Agostini et al. 2017) and posture (Ghislieri et al. 2019b; Agostini et al. 2019).

On the other hand, multichannel systems already proved their usability, accuracy and reliability in clinics (Agostini et al. 2014b, 2015b, d, 2018; Carlone et al. 2016). These systems are based on fully integrated solutions that include foot-switches (to directly detect gait events), electro-goniometers (to directly record joint kinematics), and surface EMG probes (to identify, non-invasively, muscle activity), all synchronized with a video recording. The multichannel STEP32 system (Medical Technology, Italy), developed at BIOLAB of Politecnico di Torino, was specifically designed for clinical gait analysis to obtain a portable solution, usable out-of-lab, at a reasonable cost (Agostini et al. 2010, 2015a, c; Gastaldi et al. 2016; Panero et al. 2018). Medical personnel can directly handle the system, without the need for demanding training or specific technical skills. However, the most important characteristic of the system are the implementation of the algorithms for Statistical Gait Analysis (Agostini et al. 2010; Agostini and Knaflitz 2011, 2012; Agostini et al. 2014a, 2020). These algorithms allow for the automatic segmentation and classification of hundreds of gait cycles collected during several minutes of overground walking, and for the user-independent processing of the muscle activation intervals, with the extraction of the most frequent muscle activation modalities. This helps a correct handling of the high intra-subject variability characterizing EMG patterns during a "natural" walking task, i.e., overground. Notice that constraining the subject to walk on a treadmill is a technical stratagem frequently used to bypass the stride-to-stride variability characterizing natural gait. The STEP32 system avoids the necessity to constrain the subject to treadmill walking (the use of which is not always advisable in clinics). The system also avoids the necessity of any manual selection of a few representative gait cycles from an overground walk, subjectively chosen by an expert.

New advances in the processing of EMG signals in pseudo-periodic human movements (e.g., walking, cycling, running, and swimming) showed that it might be important to distinguish between principal and secondary muscle activations (Rimini et al. 2017b; Ghislieri et al. 2020a). Principal activations are those muscle activations strictly necessary to perform the motor task under study, i.e., indispensable to obtain the various phases of each cyclic biomechanical output. Secondary activations are auxiliary activations that may be present in some of the movement cycles (and absent in the rest of the cycles): these extemporary actuations of the muscles have the role to adjust motor outputs in presence of internal or external disturbances or increased stabilization needs. Recently, the BIOLAB team developed the CIMAP algorithm (Clustering for Identification of Muscle Activation Patterns) to group the movement cycles sharing similar timing patterns (Rosati et al. 2017a), providing a technical base to extract principal and secondary activations during locomotion. This methodological procedure allows for obtaining robust indexes helpful in clinics, such as the EMG asymmetry index (Castagneri et al. 2018, 2019).

Current trends in literature hypothesize that the Central Nervous System (CNS) controls the muscle-skeletal system through muscle synergies (Tresch et al. 2006; Torres-Oviedo and Ting 2010; Taborri et al. 2018; Ghislieri et al. 2020b, c), sequentially co-activating group of muscles, triggered by neural commands bursting at specific timings of the movement cycle. This is a promising way to study motor control in a quantitative, non-invasive manner. In particular, studying muscle synergies allows obtaining a deeper understanding about the "programme" through which the CNS guides the moving body. Again, this might have important applications in the management of patients affected by neurological disorders altering motor patterns. Furthermore, neurofeedback, neurorehabilitation through human–robot interfaces, and myoelectric control of robotic exoskeletons are among the most important research frontiers that are quickly developing in this field.

This contribution aims to review the main methodologies developed during the last decade, in the field of "Statistical Gait Analysis" and of the body of knowledge developed in the advanced processing of surface EMG signal collected during gait, to help the clinical interpretation of abnormal motor patterns, and the extraction of principal and secondary activations. Furthermore, this chapter introduces how an in-depth study of muscle synergies might provide new insights into the understanding of patients' motor-control strategies.

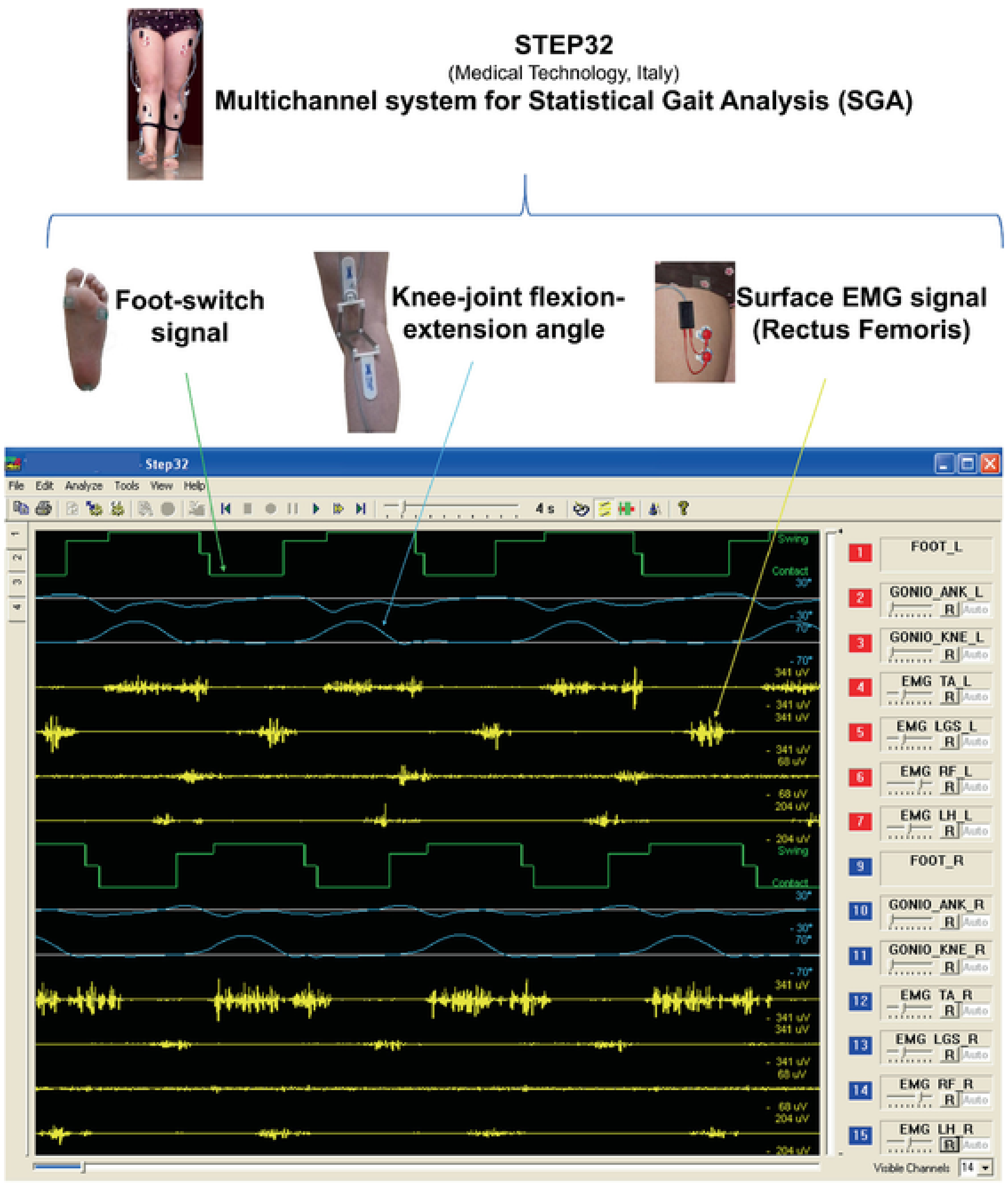
2. Statistical Gait Analysis

Traditional gait analysis most frequently analyzes only a few gait AQ3 cycles of a subject's walk. The tested subjects are typically required to hit two force platforms placed at a short distance, one for each foot (the entire sole of the subject's foot must be placed on each platform), while their motion is recorded by a set of stereophotogrammetric video-cameras. However, this procedure frequently does not allow for capturing the natural walk of the subject and its cycle-to-cycle variability, featuring human locomotion.

New trends in gait analysis prescribes to take into account several hundreds of consecutive steps: this allows describing gait from a statistical point of view. In this case, results are highly repeatable and user-independent. This procedure is known as "Statistical Gait Analysis" (SGA) (Agostini et al. 2010) and requires the automatic analysis of gait signals continuously recorded for 3–5 min. This procedure provides accurate measures of time-distance parameters, joint kinematics, and muscle activation patterns. The multichannel system STEP32 was designed to perform SGA in the clinical setting and includes (Fig. 1):

Fig. 1

The multichannel system STEP32 (Medical Technology, Italy) includes foot-switches, electrogoniometers and surface EMG probes to acquire gait signals. In this example, 14 channels are used, 7 for each lower limb: they are highlighted by a red square for the left side, and by a blue square for the right side. For each side, the system has recorded 1 foot-switch or "basographic" signal (displayed in green), 2 joint kinematic signals of the ankle and knee joints in the sagittal plane (displayed in cyan), and 4 surface EMG signals from the main lower-limb muscles, i.e. Tibialis Anterior (TA), Gastrocnemius Lateralis (LGS), Rectus Femoris (RF) and Lateral Hamstrings (LH) (displayed in yellow)



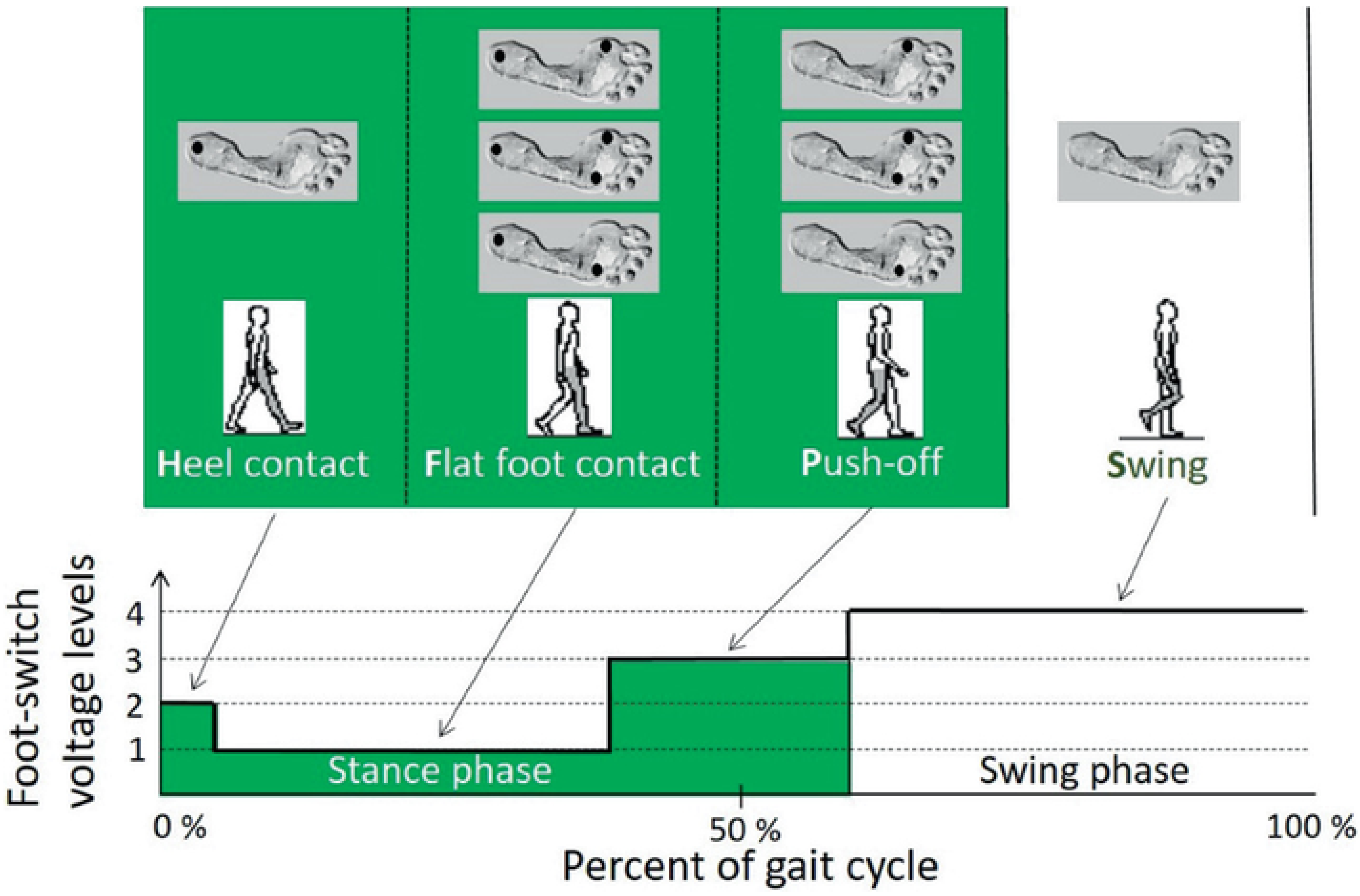
- Foot-switches to measure the foot-floor contact and detect gait phases;
- Electro-goniometers to measure the kinematic angles of the joints (ankle, knee, and hip), during gait;
- Surface EMG probes to acquire the electrical signals from the muscles in a non-invasive manner, during gait.

An example of the signals acquired during a walk is provided on the right panel of Fig. 1.

Usually, 3 foot-switches are attached to the sole (beneath the heel, 1st, and 5th metatarsal heads). Since each foot-switch has 2 possible states (open/close), they overall provide 2^3 = 8 combinations of possible voltage levels (8-level basography). However, it is generally preferred a simplified version in which only 4 levels are considered (4-level basography). These 4 levels correspond to the following gait phases (Fig. 2):

Fig. 2

HFPS is the most common gait cycle observed in healthy subjects. It consists of the following sequence of foot-floor contact sub-phases of stance: heel contact–flat foot contact–push-off (H-F-P), followed by swing (S)



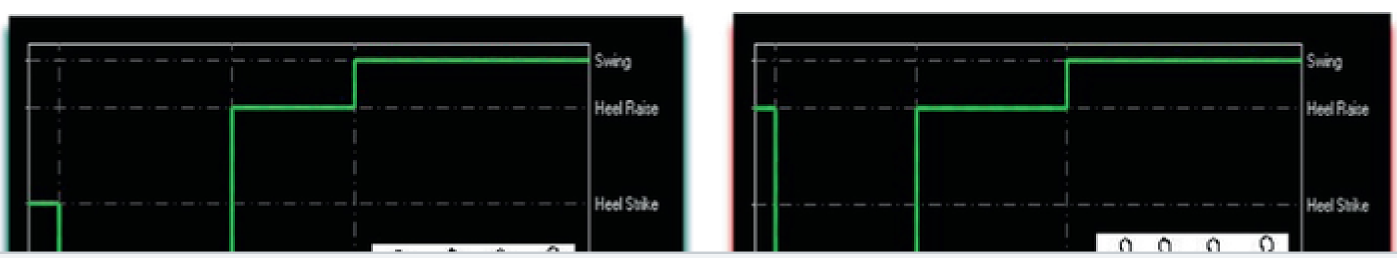
- Heel contact (H) → only the switch under the heel is closed;
- Flat-foot contact (F) → the heel-switch is closed, and at least one of the metatarsal-head switches are also closed;
- Heel-off or Push-off (P) → at least one of the metatarsal-head switches are closed;
- Swing (S) → all foot-switches are open (the foot is raised from floor).

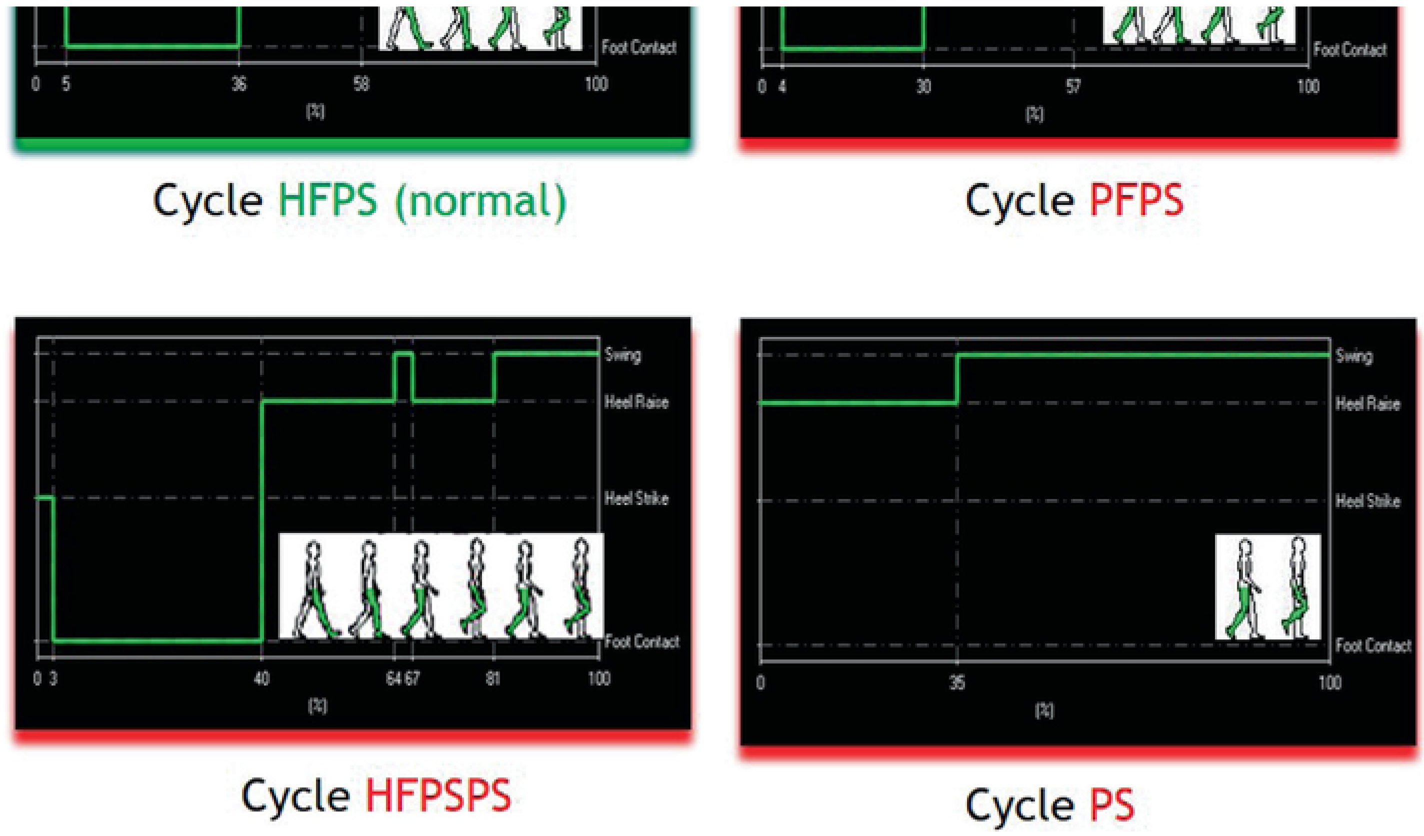
Identifying these 4 levels during locomotion allows for detecting the sequence of foot-floor contact phases and their duration. Furthermore, the 4-level basography provides the base for the automatic segmentation of gait signals into separate gait cycles.

The gait cycle is the sequence of biomechanical events between two consecutive initial supports (or "strikes") of the foot from the same lower limb. The sequence HFPS is the most common gait cycle observed in healthy subjects, and can be considered the "normal" or "typical" gait cycle. However, gait cycles can be composed of other sequences of gait phases, different from the normal one, called "atypical" cycles, which can be prevalent in the pathological gait (Fig. 3). For example, in subjects with equine foot, the cycle usually begins with a forefoot strike, instead of a heel strike. In many neuro-degenerative diseases (such as cerebral stroke, Parkinson's disease, multiple sclerosis, and muscular dystrophy) patients can display foot-drop during the swing phase. The analysis of "long" walks of at least 100–250 consecutive gait cycles shows that both typical and atypical cycles may be present, both in pathological and healthy subjects. In healthy subjects, it is usual to observe up to 5–10% atypical cycles, especially if direction changes are part of the acquisition. In pathological subjects, depending on the pathology, the occurrence percentage of atypical cycles can significantly increase, up to 100%, in severely compromised subjects. Hence, it is important to segment and classify all the different types of gait cycles, as well as their frequency of occurrence. Indeed, different gait cycles involve different patterns of muscle activation. Therefore, muscle activation patterns must be studied separately for each gait-cycle type. Moreover, in pathological subjects, even in presence of normal cycles, the phases H, F, P, and S, may have altered duration (augmented or shortened) with respect to the corresponding phases of healthy subjects. The precise knowledge of the duration of the sub-phases of stance (H, F, and P) provide additional spatio-temporal parameters, with respect to those usually found in the literature, which can be useful in clinics.

Fig. 3

Different kinds of gait cycles are displayed: the normal gait cycle (HFPS), and some examples of atypical gait cycles (PFPS, PS, HFPSPS). In particular, both PSPS and PS cycles are characterized by a forefoot strike, typical of hemiplegic gait. In HFPSPS cycles, the forefoot drops during the swing phase (indicating insufficient foot clearance)

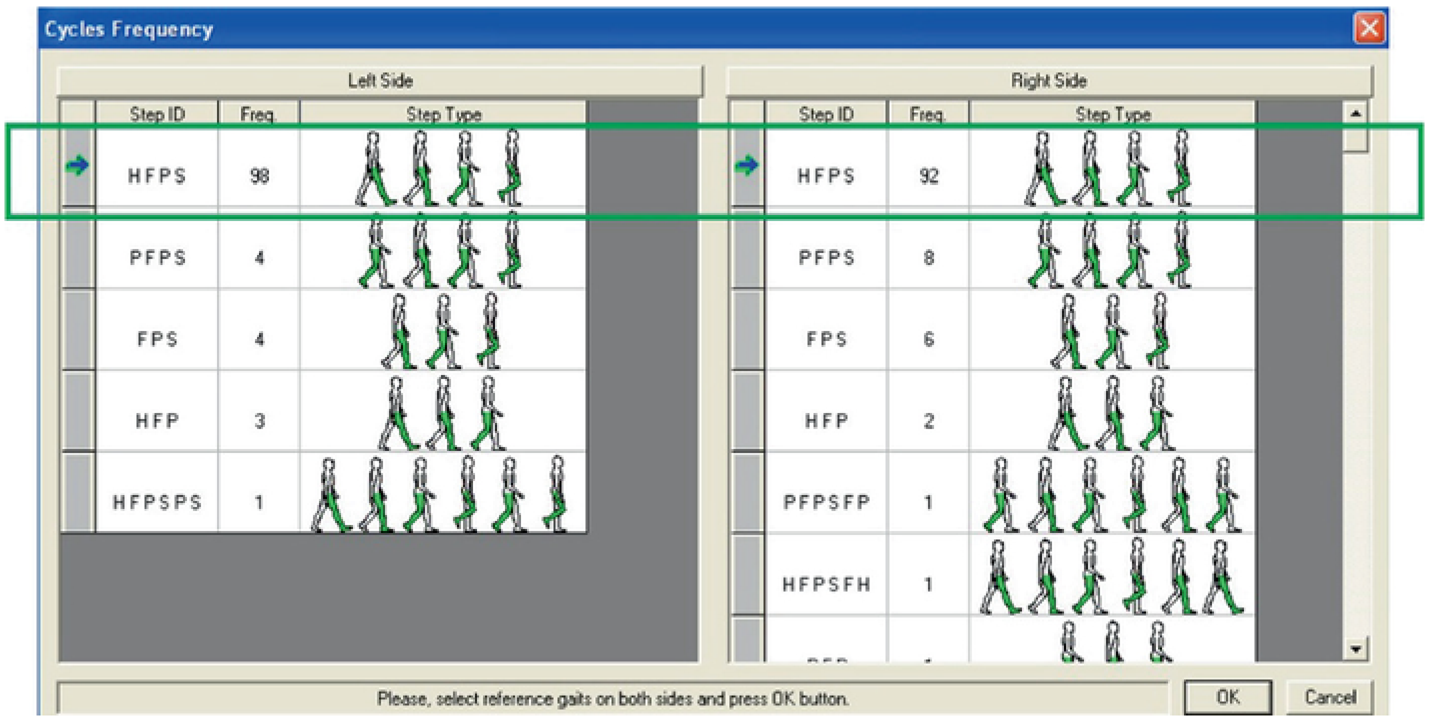




Therefore, the first step towards the statistical analysis of gait is the identification of all the different cycles of a walk. This task can be performed automatically, without user-interaction (Fig. 4). Then, the average joint kinematics and muscle activation patterns are obtained, separately for each specific gait cycle typology.

Fig. 4

Example of selection of gait cycles in a healthy subject. An arrow indicates the typical gait cycles observed on the left and on the right side (the most frequent cycles)



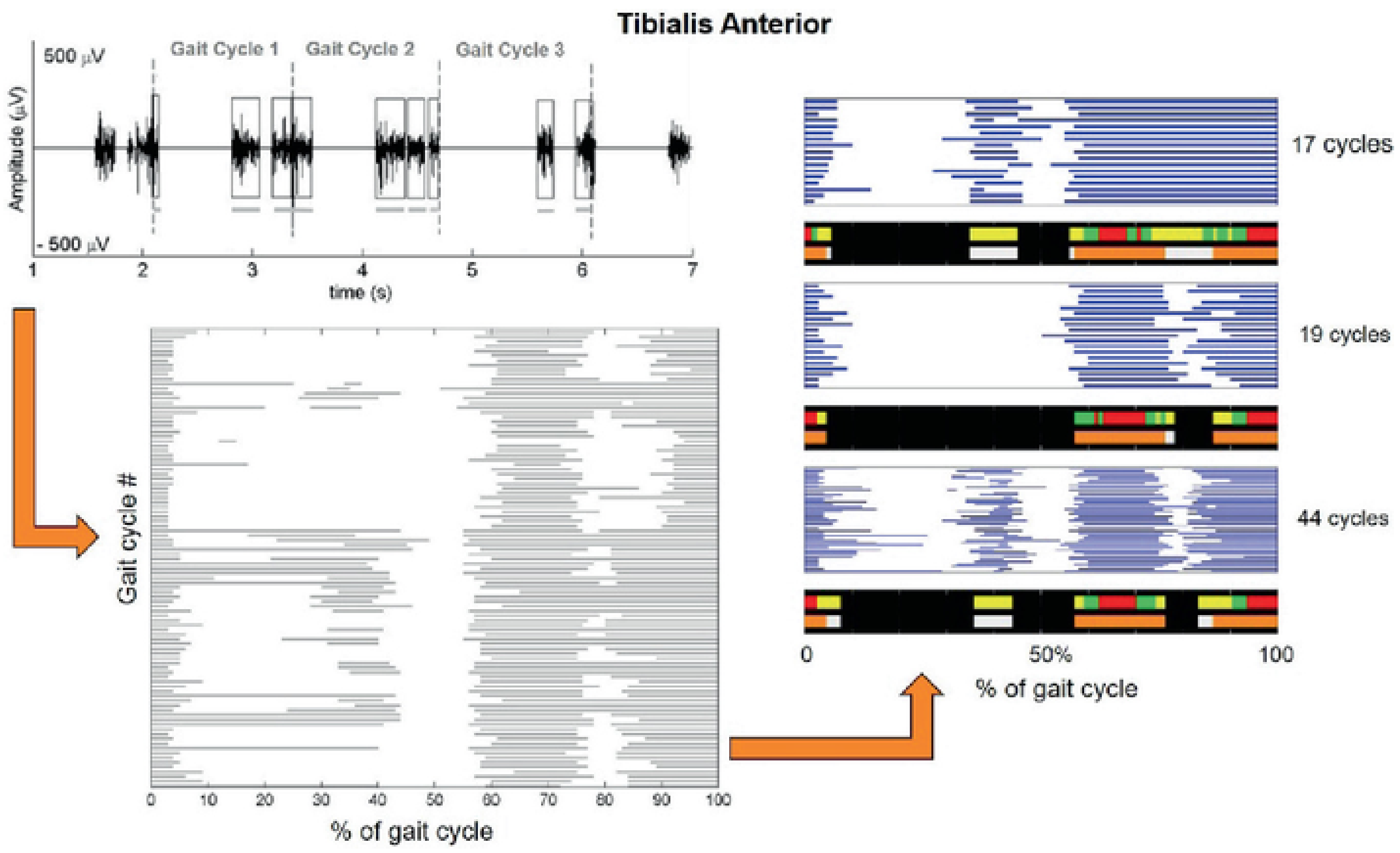
3. Principal and Secondary Activations

In spite of the above-described efforts to manage EMG variability, this latest remains very high, even when analyzing normal locomotion. For a specific subject's muscle, different activation patterns are usually present during gait, each characterized by a specific frequency of occurrence (Di Nardo et al. 2017). This makes it difficult the interpretation of clinical results. Indeed, the high stride-to-stride variability is one of the key factors that limited the widespread use of EMG in clinical gait analysis (Agostini et al. 2020). To overcome this limitation, the CIMAP algorithm was designed to cluster similar EMG cyclic patterns (Rosati et al. 2017a, b). Afterwards, in post-processing, it is possible to separate principal from secondary activations, i.e., distinguish the essential muscle activations required to perform the motor task from the aleatory adjustments also recorded in the EMG signals. In Fig. 5 it is displayed an example of principal and secondary activations extracted from a series of gait cycles collected during a subject's walk. Extracting principal activations allows for obtaining accurate and repeatable features from EMG gait patterns, both in healthy and pathological subjects. These features are useful to build robust and reliable indexes helping the clinical interpretation of gait data. As an example, this methodology was used to define an EMG asymmetry index characterizing gait, that was then validated on different cohorts of orthopedic patients (implanted with knee megaprosthesis after bone tumor resection, or implanted with hip or knee prostheses for osteoarthritis treatment), neurological patients (elderly subjects affected by idiopathic normal pressure hydrocephalus and hemiplegic children after cerebral palsy), as well as healthy subjects of different ages (elderly, adults, and children) (Castagneri et al. 2019).

Fig. 5

Example of extraction of principal activations from the EMG signal of a Tibialis Anterior muscle (collected during a walk of a healthy subject). First, the muscle activations are detected for each gait cycle. Second, the activation interval dataset is prepared

time-normalizing each gait cycle. Third, gait cycles are grouped into clusters sharing similar timing patterns, and the prototype of each cluster is calculated. Then, the principal activations are obtained as the intersection of the clusters' prototypes. Hence, principal activations are the "common intervals" of the prototypes, displayed as orange bars (secondary activations are displayed as white bars)

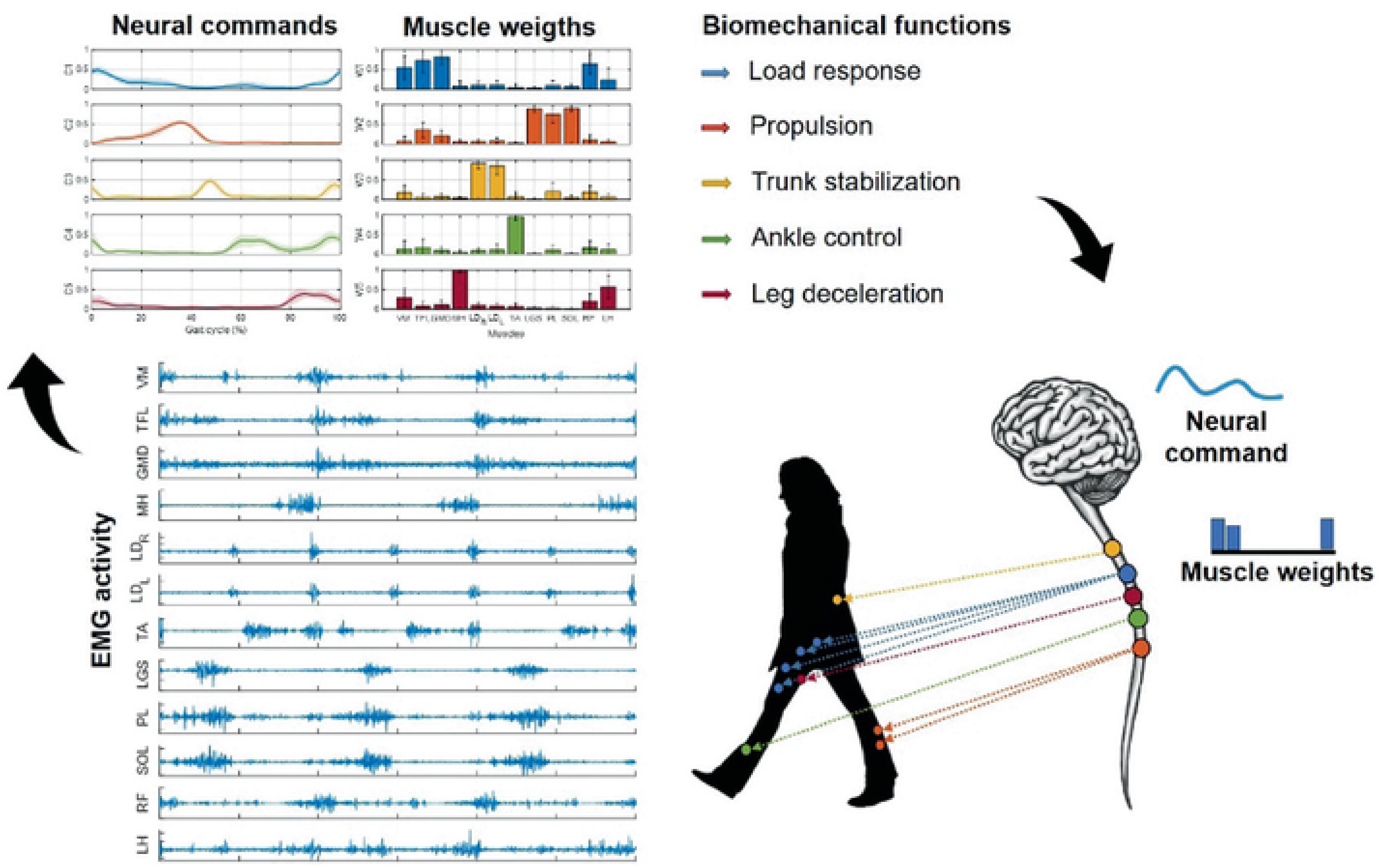


4. Muscle Synergies

Recording EMG signals from a set of 12 muscles of the lower limb and the trunk, and applying a reduction algorithm, typically the Non-Negative Matrix Factorization (NNMF) algorithm (Tresch et al. 2006), locomotion can be described by 5 muscle synergies, each corresponding to a specific and clearly recognizable biomechanical function (Rimini et al. 2017a). In other words, the matrix of EMG signals collected, non-invasively, during gait can be "reverse engineered" to unravel the neural commands issued by the CNS to specific group of muscles, properly weighted (see Fig. 6). Each muscle synergy (or "motor module") comprises:

Fig. 6

Reverse engineering of neural commands. From EMG signals recorded during gait, it is possible to extract muscle synergies (neural commands and muscle weights of each motor module)



- Time-dependent activation coefficients ("neural commands"), expressed as a percentage of the gait cycle;
- Time-independent weights (defining which muscles are active in the synergy and quantifying their amount of contribution to the synergy).

Muscle synergies are consistent both within and between subjects, and they are hypothesized to be the building blocks used by the CNS to produce movement.

Also in this framework, the importance of robust EMG pre-processing is essential to obtain reliable results (Ghislieri et al. 2019a), and the splitting of principal and secondary EMG activations before the extraction of muscle synergy can help the interpretation of results (Ghislieri et al. 2020a).

As a final remark on muscle synergies, it should be mentioned that they are revolutionizing not only the neurological assessment in clinics (e.g. in post-stroke subjects), but are becoming a milestone also in robotics (in robot-control design), and in sport science (in the evaluation of athletes' performance and definition of training guidelines) (Taborri et al. 2018).

5. Conclusion

This chapter is a very dense summary of the research activities that was carried out in the last decade in the advanced processing of EMG signals. It can be intended as a basic introduction to Statistical Gait Analysis, to the extraction of principal and secondary muscle activations, and to the quantitative study of motor control strategies through the extraction of muscle synergies. All the techniques and algorithms mentioned herein were published in the reported literature, where the interested reader can found the implementation details.

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