POLITECNICO DI TORINO
Repository ISTITUZIONALE

Statistical Gait Analysis Based on Surface Electromyography.

Original
Statistical Gait Analysis Based on Surface Electromyography / Agostini, V., Ghislieri, M., Rosati, S., Balestra, G., Dotti, G., Knaflitz, M. (LECTURE NOTES IN BIOENGINEERING). - In: Medicine-Based Informatics and EngineeringSTAMPA. - [s.l] : Springer, 2022. - ISBN 978-3-030-87844-3. - pp. 23-35 [10.1007/978-3-030-87845-0_2]

Availability:
This version is available at: 11583/2945915 since: 2022-01-12T15:30:32Z

Publisher:
Springer

Published
DOI:10.1007/978-3-030-87845-0_2

Terms of use:

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

Publisher copyright
Springer postprint/Author's Accepted Manuscript (book chapters)

This is a post-peer-review, pre-copyedit version of a book chapter published in Medicine-Based Informatics and Engineering. The final authenticated version is available online at: http://dx.doi.org/10.1007/978-3-030-87845-0_2

(Article begins on next page)

29 November 2026

Query Details

Back to Main Page

1. Please confirm if the inserted city name is correct. Amend if necessary.

ok

2. Please check and confirm if the authors and their respective affiliations have been correctly identified. Amend if necessary.

ok

3. Please confirm if the section headings identified are correct.

ok

Statistical Gait Analysis Based on Surface Electromyography

Valentina Agostini
Email : valentina.agostini@polito.it
Affiliationids : Aff1 Aff2, Correspondingaffiliationid : Aff1

Marco Ghislieri
Email : marco.ghislieri@polito.it
Affiliationids : Aff1 Aff2

Samanta Rosati
Email : samanta.rosati@polito.it
Affiliationids : Aff1 Aff2

Gabriella Balestra
Email : gabriella.balestra@polito.it
Affiliationids : Aff1 Aff2

Gregorio Dotti
Email : gregorio.dotti@studenti.polito.it
Affiliationids : Aff1 Aff2

Marco Knaflitz
Email : marco.knaflitz@polito.it
Affiliationids : Aff1 Aff2

Aff1 Department of Electronics and Telecommunications, Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129, Torino, Italy

Aff2 PolitoBIOMedLab, Politecnico di Torino, Torino, Italy

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

© Springer Nature

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

© Springer Nature

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.

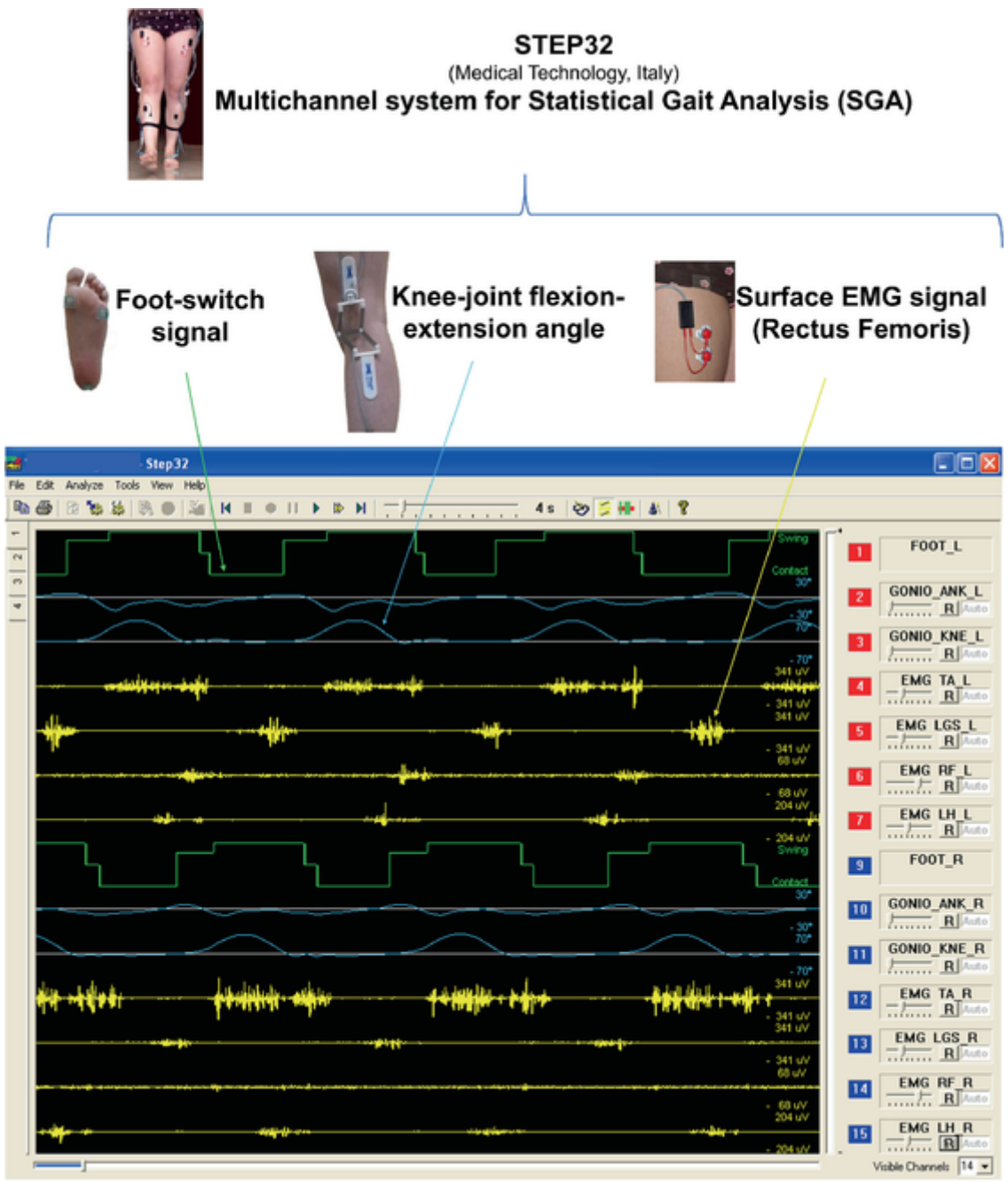
2. Statistical Gait Analysis

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.

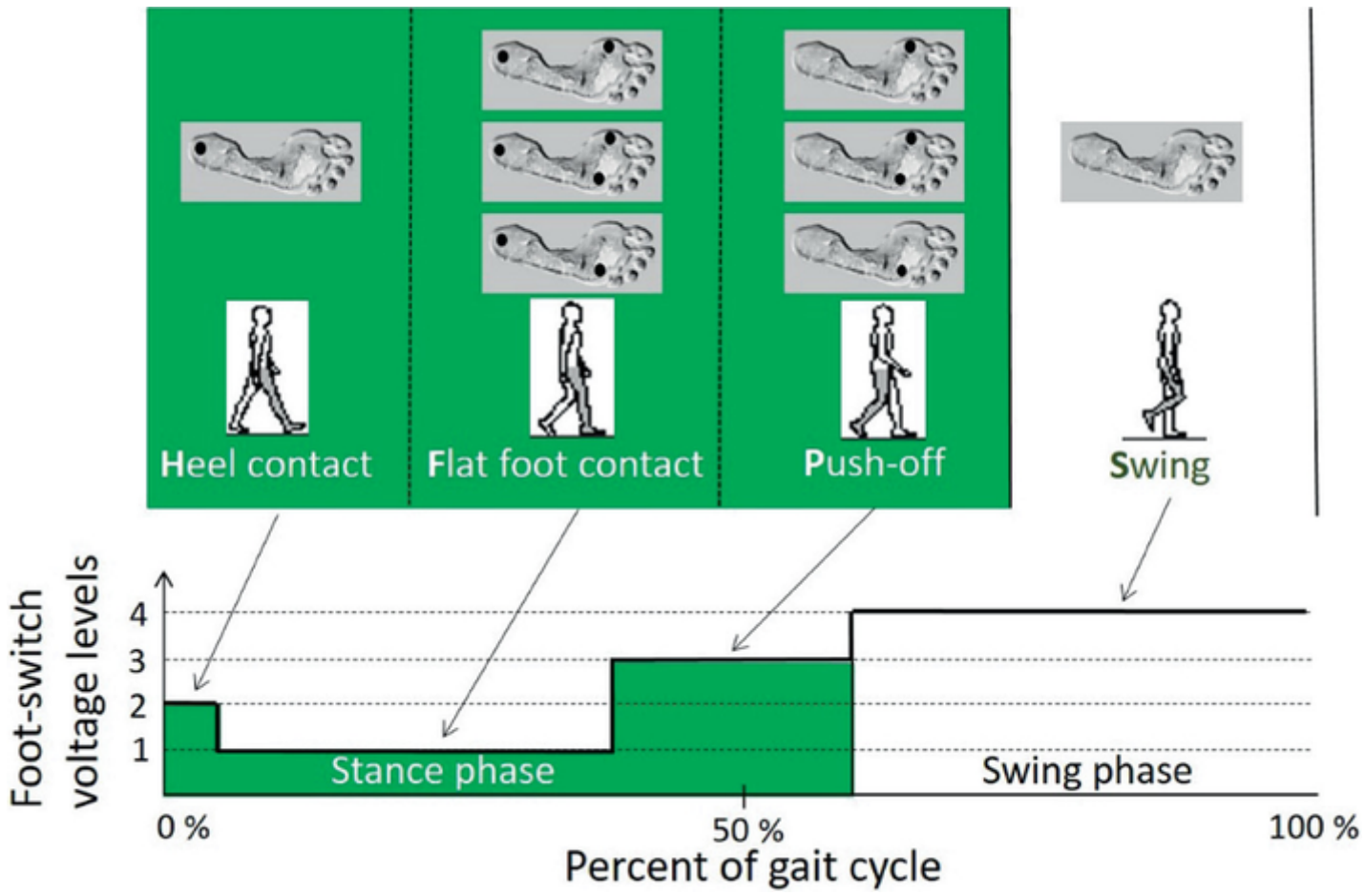
Usually, 3 foot-switches are attached to the sole (beneath the heel, 1st, and 5th metatarsal heads). Since each foot-switch has 2 possible states (open/close), they overall provide $2^3 = 8$ combinations of possible voltage levels (8-level basography). However, it is generally

© Springer Nature

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)



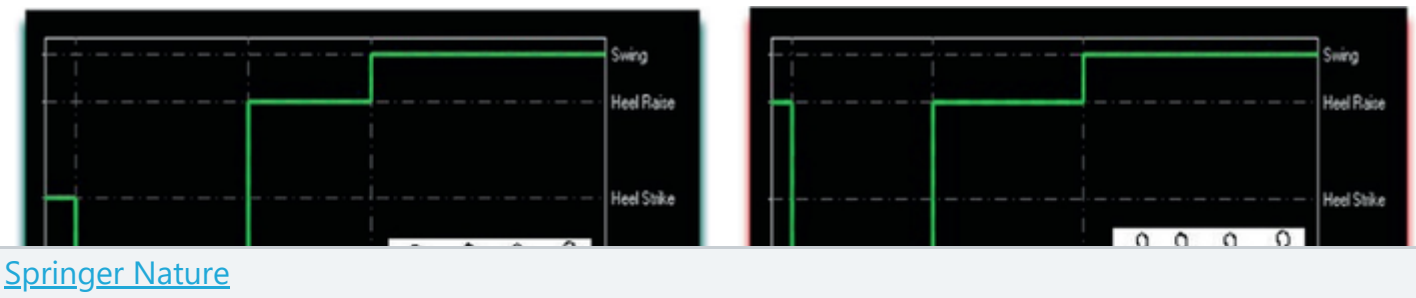
- Heel contact (H) → only the switch under the heel is closed;
- Flat-foot contact (F) → the heel-switch is closed, and at least one of the metatarsal-head switches are also closed;
- Heel-off or Push-off (P) → at least one of the metatarsal-head switches are closed;
- Swing (S) → all foot-switches are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

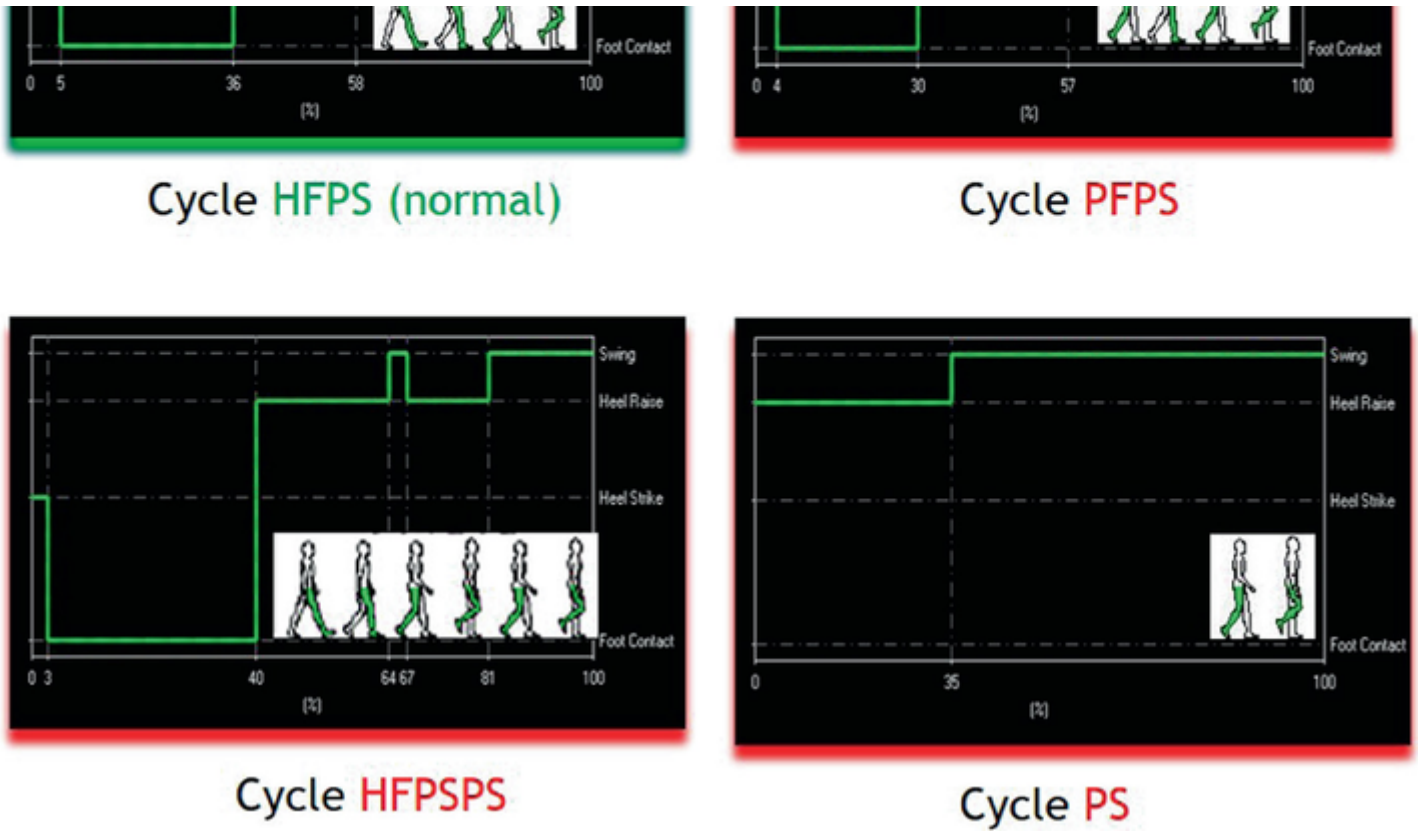
The gait cycle is the sequence of biomechanical events between two consecutive initial supports (or "strikes") of the foot from the same lower limb. The sequence HFPS is the most common gait cycle observed in healthy subjects, and can be considered the "normal" or "typical" gait cycle. However, gait 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)



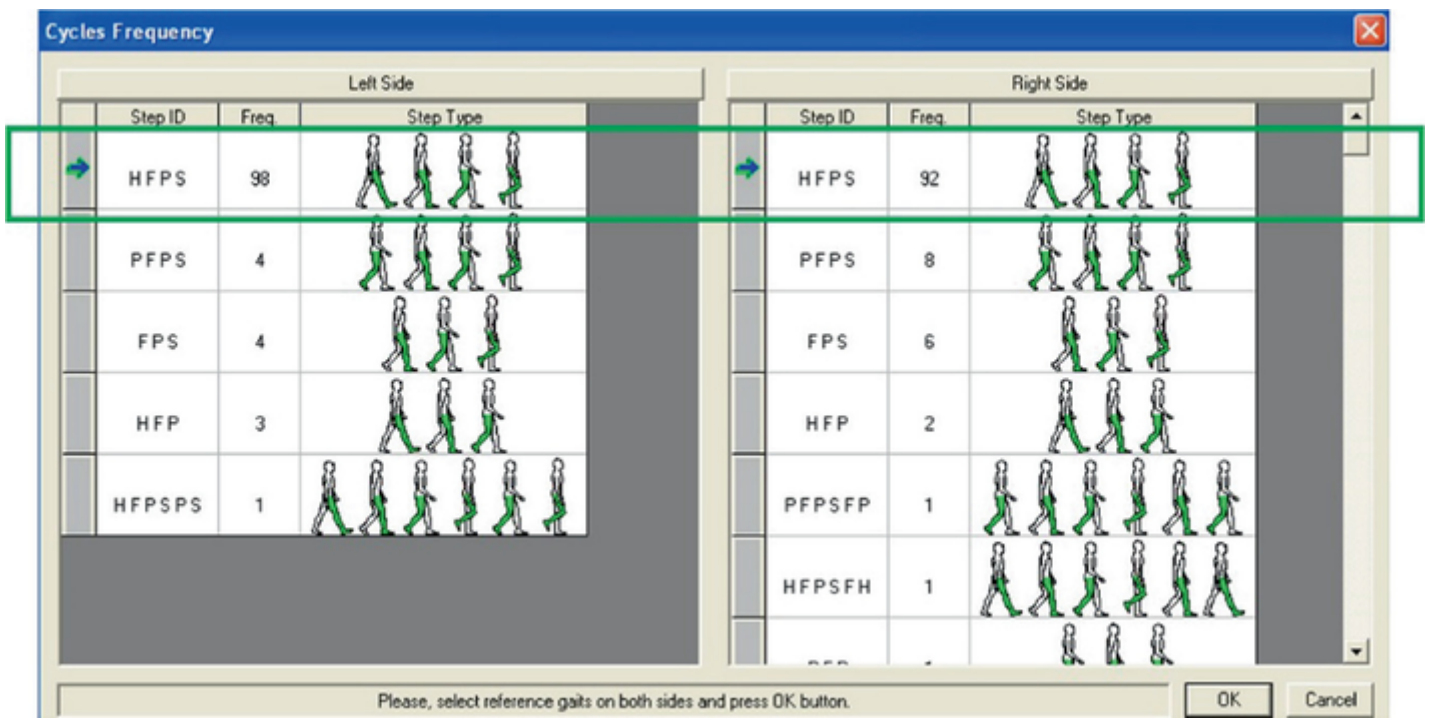
© Springer Nature



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

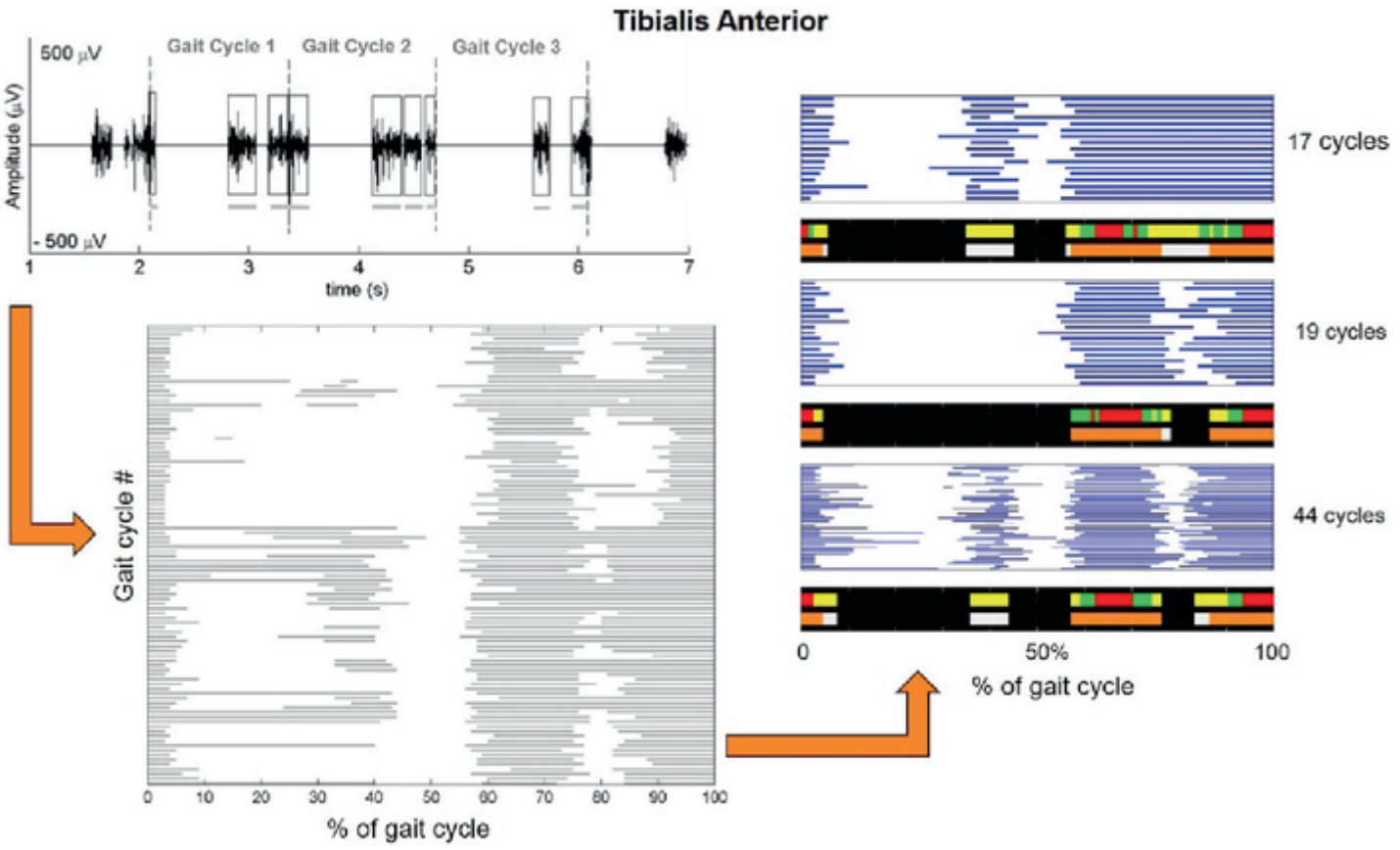
In spite of the above-described efforts to manage EMG variability, this latest remains very high, even when analyzing normal locomotion. For a specific subject's muscle, different activation patterns are usually present during gait, each characterized by a specific frequency of occurrence (Di Nardo et 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

© Springer Nature

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)

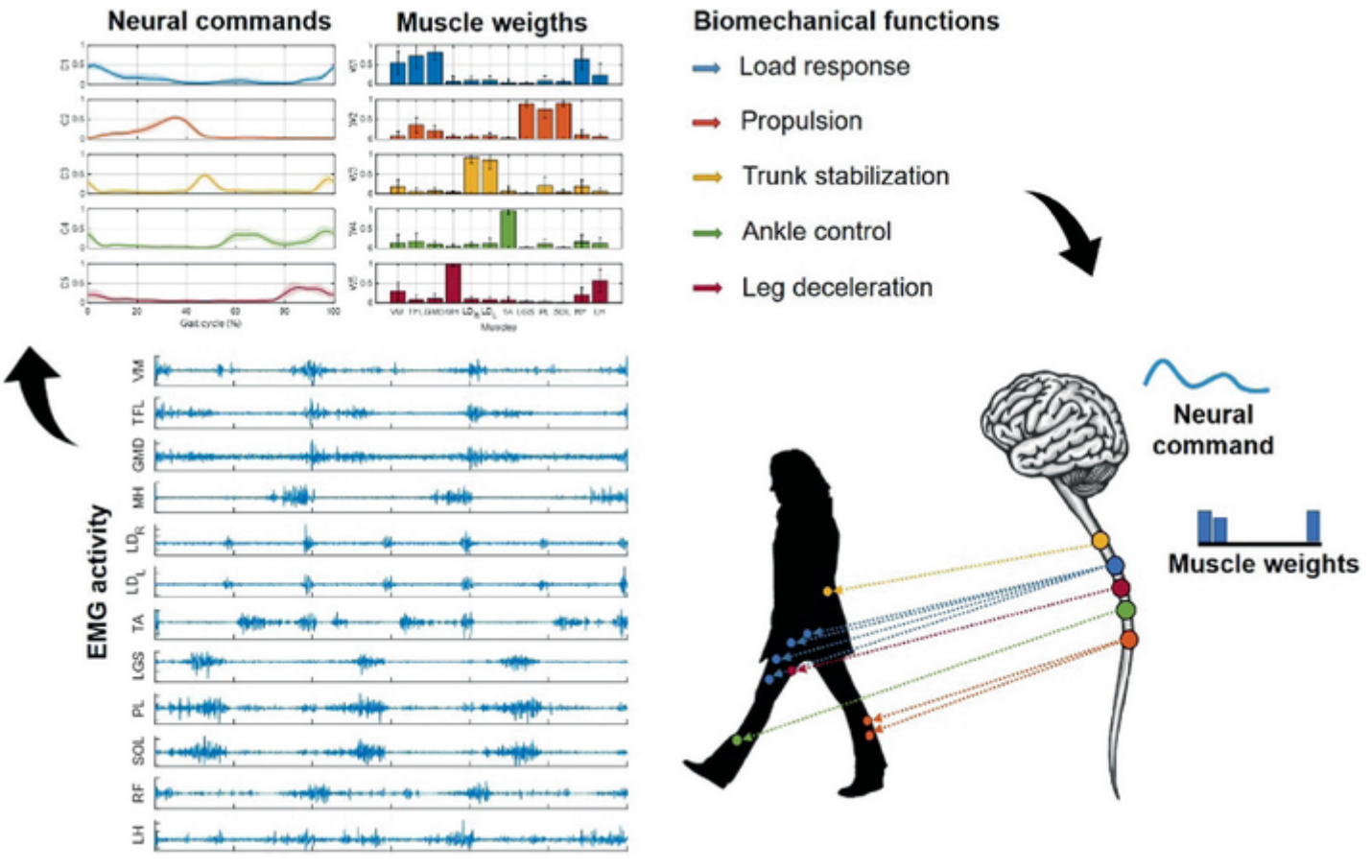


4. Muscle Synergies

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.

© Springer Nature

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.

Acknowledgements

I thank you very much prof. Franco Simini for inviting me as a keynote speaker at the 22th Biomedical Engineering Congress SABI 2020, held in Piriápolis (Uruguay), on 4–6 March 2020. The material summarized in this chapter was presented during the invited talk.

References

Agostini V, Knaflitz M (2011) Statistical gait analysis. In: Acharya UR, Molinari F, Tamura T et al (eds) Distributed diagnosis and home healthcare, pp 99–121

Agostini V, Knaflitz M (2012) An algorithm for the estimation of the signal-to-noise ratio in surface myoelectric signals generated during cyclic movements. IEEE Trans Biomed Eng 59:219–225. https://doi.org/10.1109/TBME.2011.2170687

Agostini V, Nascimbeni A, Gaffuri A et al (2010) Normative EMG activation patterns of school-age children during gait. Gait Posture 32:285–289. https://doi.org/10.1016/j.gaitpost.2010.06.024

Agostini V, Chiaramello E, Bredariol C et al (2011) Postural control after traumatic brain injury in patients with neuro-ophthalmic deficits. Gait Posture 34:248–253. https://doi.org/10.1016/j.gaitpost.2011.05.008

Agostini V, Chiaramello E, Knaflitz M et al (2013) Circular components in center of pressure signals. Mot Control 17:355–369

Agostini V, Balestra G, Knaflitz M et al (2014a) Segmentation and classification of gait cycles. IEEE Trans Neural Syst Rehabil Eng 22:946–952. https://doi.org/10.1109/TNSRE.2013.2291907

Agostini V, Ganio D, Facchin K et al (2014b) Gait parameters and muscle activation patterns at 3, 6 and 12 months after total hip arthroplasty. J Arthroplasty 29:1265–1272. https://doi.org/10.1016/j.arth.2013.12.018

Agostini V, Knaflitz M, Antenucci L et al (2015a) Wearable sensors for gait analysis. 2015 IEEE Int Symp Med Meas Appl Proc 146–150. https://doi.org/10.1109/MeMeA.2015.7145189

Agostini V, Lanotte M, Carlone M et al (2015b) Instrumented gait analysis for an objective pre-/postassessment of tap test in normal pressure hydrocephalus. Arch Phys Med Rehabil 96:1235–41. https://doi.org/10.1016/j.apmr.2015.02.014

Agostini V, Lo Fermo F, Massazza G, Knaflitz M (2015c) Does texting while walking really affect gait in young adults? J Neuroeng Rehabil 12:86. https://doi.org/10.1186/s12984-015-0079-4

Agostini V, Nascimbeni A, Gaffuri A et al (2015d) Multiple gait patterns within the same Winters class in children with hemiplegic cerebral palsy. Clin Biomech 30:908–914. https://doi.org/10.1016/j.clinbiomech.2015.07.010

Agostini V, Sbrollini A, Cavallini C et al (2016) The role of central vision in posture: postural sway adaptations in Stargardt patients. Gait Posture 43:233–238. https://doi.org/10.1016/j.gaitpost.2015.10.003

Agostini V, Gastaldi L, Rosso V et al (2017) A wearable magneto-inertial system for gait analysis (H-Gait): validation on normal weight and overweight/obese young healthy adults. Sensors 17:2406. https://doi.org/10.3390/s17102406

© Springer Nature

Agostini V, Rimini D, Ghislieri M et al (2018) Muscle synergies in patients with low back pain: a statistical gait analysis study pre- and post-rehabilitation. In: 2018 IEEE international symposium on medical measurements and applications (MeMeA). IEEE, pp 1–6

Agostini V, Aiello E, Fortunato D et al (2019) A wearable device to assess postural sway. In: 2019 IEEE 23rd international symposium on consumer technologies, ISCT 2019. IEEE, pp 197–200

Agostini V, Ghislieri M, Rosati S et al (2020) Surface electromyography applied to gait analysis: how to improve its impact in clinics? Front Neurol 11:994. https://doi.org/10.3389/fneur.2020.00994

Carlone M, Re A, Massazza G et al (2016) Wearable sensors for gait analysis in the clinical setting: rehabilitation outcomes measures after vestibular schwannoma surgery. Int J Appl Eng Res 11:10484–10489

Castagneri C, Agostini V, Balestra G et al (2018) Emg asymmetry index in cyclic movements. In: 2018 IEEE life sciences conference, LSC 2018. IEEE, pp 223–226

Castagneri C, Agostini V, Rosati S et al (2019) Asymmetry index in muscle activations. IEEE Trans Neural Syst Rehabil Eng 27:772–779. https://doi.org/10.1109/TNSRE.2019.2903687

Cimolin V, Galli M (2014) Summary measures for clinical gait analysis: a literature review. Gait Posture 39:1005–1010. https://doi.org/10.1016/j.gaitpost.2014.02.001

Di Nardo F, Mengarelli A, Strazza A et al (2017) A new parameter for quantifying the variability of surface electromyographic signals during gait: the occurrence frequency. J Electromyogr Kinesiol 36:25–33. https://doi.org/10.1016/j.jelekin.2017.06.006

De Leonardis G, Rosati S, Balestra G et al (2018) Human activity recognition by wearable sensors. In: 2018 IEEE international symposium on medical measurements and applications (MeMeA) proceedings. IEEE (in press)

Frigo C, Crenna P (2009) Multichannel SEMG in clinical gait analysis: a review and state-of-the-art. Clin Biomech 24:236–245

Gastaldi L, Agostini V, Takeda R et al (2016) Evaluation of the performances of two wearable systems for gait analysis: a pilot study. Int J Appl Eng Res 11:8820–8827

Ghislieri M, Agostini V, Knaflitz M (2019a) How to improve robustness in muscle synergy extraction. In: Proceedings of the annual international conference of the IEEE engineering in medicine and biology society, EMBS. IEEE, pp 1525–1528

Ghislieri M, Gastaldi L, Pastorelli S et al (2019b) Wearable inertial sensors to assess standing balance: a systematic review. Sensors 19:4075. https://doi.org/10.3390/s19194075

Ghislieri M, Agostini V, Knaflitz M (2020a) Muscle synergies extracted using principal activations: improvement of robustness and interpretability. IEEE Trans Neural Syst Rehabil Eng 1–1. https://doi.org/10.1109/TNSRE.2020.2965179

Ghislieri M, Knaflitz M, Labanca L et al (2020b) Muscle synergy assessment during single-leg stance. IEEE Trans Neural Syst Rehabil Eng 28. https://doi.org/10.1109/TNSRE.2020.3030847

Ghislieri M, Knaflitz M, Labanca L et al (2020c) Methodological issues in the assessment of motor control during single-leg stance. In: IEEE medical measurements and applications, MeMeA 2020—conference proceedings. Institute of Electrical and Electronics Engineers Inc.

Panero E, Digo E, Agostini V, Gastaldi L (2018) Comparison of different motion capture setups for gait analysis: validation of spatio-temporal parameters estimation. In: 2018 IEEE international symposium on medical measurements and applications (MeMeA). IEEE, pp 1–6

Perry J (1992) Gait analysis: normal and pathological function. SLACK Incorporated, Thorofare, New Jersey

Rimini D, Agostini V, Knaflitz M et al (2017a) Intra-subject consistency during locomotion: similarity in shared and subject-specific muscle synergies. Front Hum Neurosci 11:586. https://doi.org/10.3389/fnhum.2017.00586

© Springer Nature

Rimini D, Agostini V, Rosati S et al (2017b) Influence of pre-processing in the extraction of muscle synergies during human locomotion. In: Proceedings of the annual international conference of the IEEE engineering in medicine and biology society, EMBS. IEEE, pp 2502–2505

Rosati S, Agostini V, Knaflitz M et al (2017a) Muscle activation patterns during gait: a hierarchical clustering analysis. Biomed Signal Process Control 31:463–469. https://doi.org/10.1016/j.bspc.2016.09.017

Rosati S, Castagneri C, Agostini V et al (2017b) Muscle contractions in cyclic movements: optimization of CIMAP algorithm. In: Proceedings of the annual international conference of the IEEE engineering in medicine and biology society, EMBS. Institute of Electrical and Electronics Engineers Inc., pp 58–61

Sbrollini A, Agostini V, Cavallini C et al (2020) Postural data from Stargardt's syndrome patients. Data Br 105452. https://doi.org/10.1016/j.dib.2020.105452

Taborri J, Agostini V, Artemiadis PK et al (2018) Feasibility of muscle synergy outcomes in clinics, robotics, and sports: a systematic review. Appl Bionics Biomech 2018

Tao W, Liu T, Zheng R, Feng H (2012) Gait analysis using wearable sensors. Sensors (Basel) 12:2255–2283. https://doi.org/10.3390/s120202255

Torres-Oviedo G, Ting LH (2010) Subject-specific muscle synergies in human balance control are consistent across different biomechanical contexts. J Neurophysiol 103. https://doi.org/10.1152/jn.00960.2009

Tresch MC, Cheung VCK, d'Avella A (2006) Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets. J Neurophysiol 95:2199–2212. https://doi.org/10.1152/jn.00222.2005

© Springer Nature