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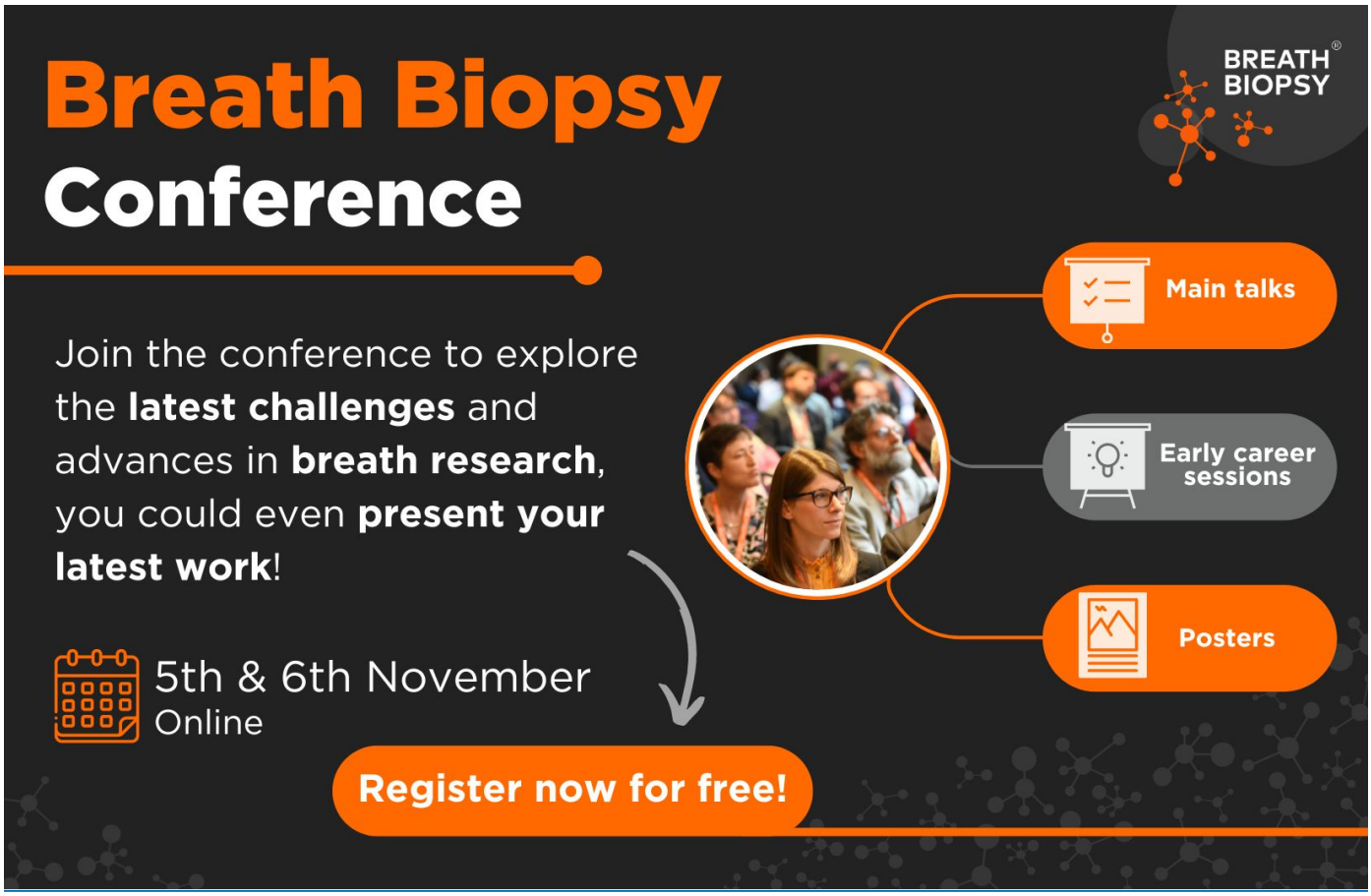

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PAPER

An open-source toolbox for enhancing the assessment of muscle activation patterns during cyclical movements

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Keywords: clustering, cyclical movements, EMG, machine learning, muscle activation patterns

Abstract

Objective. The accurate temporal analysis of muscle activations is of great importance in several research areas spanning from the assessment of altered muscle activation patterns in orthopaedic and neurological patients to the monitoring of their motor rehabilitation. Several studies have highlighted the challenge of understanding and interpreting muscle activation patterns due to the high cycle-by-cycle variability of the sEMG data. This makes it difficult to interpret results and to use sEMG signals in clinical practice. To overcome this limitation, this study aims at presenting a toolbox to help scientists easily characterize and assess muscle activation patterns during cyclical movements. *Approach.* CIMAP (Clustering for the Identification of Muscle Activation Patterns) is an open-source Python toolbox based on agglomerative hierarchical clustering that aims at characterizing muscle activation patterns during cyclical movements by grouping movement cycles showing similar muscle activity. *Main results.* From muscle activation intervals to the graphical representation of the agglomerative hierarchical clustering dendrograms, the proposed toolbox offers a complete analysis framework for enabling the assessment of muscle activation patterns. The toolbox can be flexibly modified to comply with the necessities of the scientist. CIMAP is addressed to scientists of any programming skill level working in different research areas such as biomedical engineering, robotics, sports, clinics, biomechanics, and neuroscience. CIMAP is freely available on GitHub (https://github.com/Biolab-PoliTO/CIMAP). *Significance.* CIMAP toolbox offers scientists a standardized method for analyzing muscle activation patterns during cyclical movements.

1. Introduction

Surface electromyography (sEMG) is commonly used, in several research areas, to quantitatively and non-invasively assess dynamic muscle activity in both physiological and pathological conditions. Among the most studied sEMG-derived parameters, the identification of the onset and offset instants of muscle activity plays a fundamental role. The assessment of sEMG activation intervals achieved great interest among researchers in a wide variety of clinical, robotic, and sports applications. In particular, muscle activation intervals are used to assess altered sEMG patterns in patients affected by orthopaedic or neurological diseases (Castagneri *et al* 2019, Hsu *et al* 2019), to define rehabilitation protocols tailored to the patient needs (Akef Khowailed and Abotabl 2019), to study posture control (Labanca *et al* 2021), to control prostheses and exoskeletons (Micera *et al* 2010, Li *et al* 2023), and to evaluate return-to-sport of athletes after injury (Rocchi *et al* 2020).

However, sEMG signals during gait are characterized by high cycle-by-cycle variability that makes it difficult to interpret the results and to use sEMG data in clinical practice (Winter and Yack 1987, Agostini *et al* 2020). For a specific muscle of a subject, different activation patterns are usually assessed during cyclical movements, each of them characterized by a specific frequency of occurrence (Di Nardo *et al* 2017). Considering the walking task, even in healthy subjects, a single muscle does not show a single preferred

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pattern of activation, but up to 4-5 distinct sEMG patterns, each characterized by a different number of activation intervals occurring within the stride (Agostini *et al* 2010, 2015). To overcome this limitation, specific algorithms are needed to help scientists to easily characterize and assess muscle activation patterns during cyclical movements.

Cluster analysis may represent a useful tool for helping scientists to study the different muscle activation patterns during cyclical movements. In this perspective, CIMAP (Clustering for the Identification of the Muscle Activation Patterns) algorithm was proposed and validated in different healthy and pathological conditions (Rosati *et al* 2017a, 2017b). The CIMAP algorithm is based on agglomerative hierarchical clustering and aims at characterizing muscle activation patterns during cyclical movements by grouping movement cycles showing similar muscle activity. This algorithm requires the muscle activation intervals as input data, computed through a muscle activity detector (not included in the toolbox). It was specifically developed to assess muscle activity patterns during walking in both physiological and pathological conditions and it was successfully applied to the study of gait asymmetry in healthy, orthopaedic, and neurological patients (Castagneri *et al* 2019, Rosati *et al* 2021). Moreover, the study by Ghislieri *et al* used the CIMAP algorithm as a pre-processing step before muscle synergy extraction to evaluate human motor control during locomotion (Ghislieri *et al* 2019, 2020). Notice that the CIMAP algorithm was originally proposed for assessing gait in both physiological and pathological conditions. Nevertheless, CIMAP can be potentially applied to other cyclical movements, as cycling and reach-to-grasp movements.

In this contribution, to support researchers interested in the analysis of muscle activation patterns, we distribute an open-source Python toolbox (CIMAP) that allows for obtaining all the representative muscle activation patterns of a muscle. The number of clusters identified by the CIMAP toolbox and the cluster size (i.e., the number of elements belonging to the same cluster), may represent meaningful information in clinics, since they indicate how many sEMG patterns were found and how frequently they occur during the analyzed movement (Agostini *et al* 2014). The proposed toolbox adopts an object-oriented programming approach that allows a clear definition of a few classes incorporating data structure and data processing methods, empowering researchers to easily extend and customize the toolbox to meet specific data and protocol needs. To better describe the processing pipeline and to provide a set of practical guidelines, an example of CIMAP application is presented considering sEMG signals acquired from a lower-limb muscle of a representative healthy subject during a 5 minute walking task.

Researchers with little coding experience will find in the Python toolbox CIMAP a complete framework for the assessment of muscle activation patterns during cyclical movements, from the pre-processing of muscle activation intervals to the graphical representation of the clustering results.

2. Methods

CIMAP toolbox is implemented in Python and includes all the required steps for performing the analysis of muscle activation patterns. This toolbox incorporates functions for all the analysis steps, from data preparation to the graphical representation of the clustering results and data saving.

Figure 1 shows the workflow of the CIMAP algorithm. The following section provides a brief description of the main functions implemented within the CIMAP, including references to relevant literature:

a) *Dataset preparation*: CIMAP toolbox requires as input the muscle activation intervals (i.e., the time intervals characterized by muscle activity). Notice that this toolbox does not include a muscle activation interval detection step. Therefore, before using this toolbox, researchers should first apply a muscle activity detector. Input data should be provided in a **.csv* file containing a $M \times (N+1)$ matrix representing muscle activation intervals, with M being the number of muscles acquired and N being the number of time samples after time-normalization. From the muscle activation intervals, the onset and offset instants are extracted, representing the beginning and the end of each muscle activation, respectively. More details about input data format are freely available on the BIOLAB GitHub repository (https://biolab-polito.github.io/CIMAP/data_requirements.html);
b) *Pre-processing*: movement cycles characterized by the same number of activation intervals occurring within the cycle duration are grouped into sub-groups (or 'modalities'). Modalities characterized by a small number of movement cycles ($num.\ cycles < Th$) are considered as non-representative and thus discarded from the following analyses. Based on a previous study by Dotti *et al* (2021), the value of Th was set equal to 10 movement cycles. Notice that this value of Th was selected and optimized based on activation intervals acquired from lower-limb muscles during long-lasting walking. More details about the optimization process can be found in the study by Dotti *et al* (2021). Th value can be easily adjusted to meet specific data needs, such as a small number of movement cycles or different motor tasks;

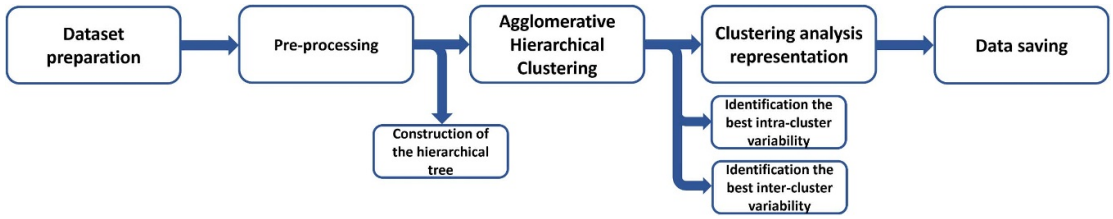

Figure 1. Schematic representation of the steps implemented within CIMAP algorithm.

c) *Agglomerative hierarchical clustering*: considering each modality separately, agglomerative hierarchical clustering is applied. From a number of clusters equal to the number of cycles belonging to the modality under consideration (i.e., each cluster is characterized by a single movement cycle), agglomerative hierarchical clustering iteratively merges the two 'closest' clusters, until a single cluster is obtained (i.e., a single cluster containing all the movement cycles belonging to the modality under consideration). The complete linkage method is used to select the two 'closest' clusters to be merged, considering both Manhattan (L_1 norm) and Chebyshev (L_∞ norm) as distance metrics (Kaufman and Rousseeuw 1990). Thus, for each modality, agglomerative hierarchical clustering is applied twice (the first time considering L_1 norm and the second time considering L_∞ norm as distance metric). The cutoff points (i.e., the final number of clusters) are selected applying to each dendrogram the cutoff rule proposed by Rosati *et al* (2017b). In particular, three cutoff points are identified to evaluate the difference (Δ_{it}) in inter-cluster distances between consecutive clustering iterations. The first cutoff point is identified as the first iteration in which the Δ_{it} is higher than the Δ_{it} average over all the iterations. The second cutoff point is identified as the first iteration in which the Δ_{it} is higher than the Δ_{it} average plus one standard deviation of Δ_{it} over all the iterations. The third cutoff point is identified as the point where the moving average of the Δ_{it} series, starting from the last iteration and moving backward, stops decreasing monotonically. Then, the best cutoff point is chosen as the one showing the lowest value in the index (CUT_IND) defined by Rosati *et al* (2017b) as follows:

$$\text{CUT_IND} = \frac{\sum_{i=1}^{n} \text{INTRA_VAR}_i * n}{\sum_{i=1}^{n} C_i} \tag{1}$$

where INTRA_VAR_i represents the intra-cluster variability of the ith cluster calculated as the mean pairwise distance between cycles, n represents the number of meaningful clusters (defined as those with more than one element), and C_i is the number of cycles included in the ith meaningful cluster. Finally, after comparing the dendrograms obtained considering the L_1 norm and L_∞ norm metrics, the one showing the lowest intra-cluster variability is selected for the following analyses;

d) *Clustering analysis representation*: this toolbox includes several visualization methods that allow for the examination of data throughout the entire analysis process. In particular, dendrograms showing clustering results can be represented for each muscle and each modality, separately. An example of clustering results representation is provided in figure 5;

e) *Data saving*: to increase the accessibility of results, their interpretability and interoperability, clustering results can be exported in *.csv* format. More details about output data format are freely available on the BIOLAB GitHub repository (https://biolab-polito.github.io/CIMAP/data_requirements.html);

Further details about the implemented Python classes and the default setting parameters are freely available on the GitHub repository (https://github.com/Biolab-PoliTO/CIMAP).

3. Results

This section describes all the steps involved in the analysis of muscle activation patterns of a sample dataset of sEMG data acquired from two lower-limb muscles (left and right Lateral Gastrocnemius muscle) of a healthy subject during a 5-min overground walking task.

The first step is the loading of muscle activation intervals contained in the sample dataset ('input_file') through the 'data_reading' function. The 'data_reading' function can be called as follows:

```
s,muscles = CIMAP.data_reading(input_file = input_file)
```

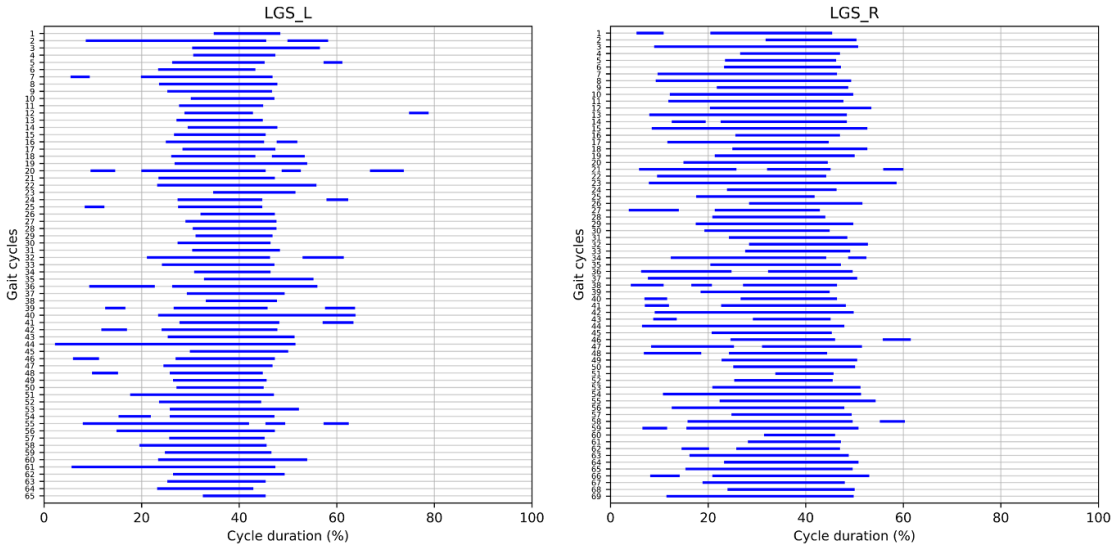

Figure 2. Example of muscle activation intervals for the left and right Lateral Gastrocnemius muscles (LGS_L and LGS_R, respectively) of a healthy volunteer during a 5-minute overground walking task. The blue horizontal lines represent muscle activation intervals expressed as a percentage of the cycle duration (BLUE = muscle active, WHITE = muscle inactive).

where *s* represents a data structure containing the muscle activation intervals to be processed through the CIMAP algorithm and muscles represents a data dictionary containing sEMG information (i.e., muscle labels, side, sensor placement, …).

Then, the 'remove_add_ints' function is called to remove (if any) outliers of muscle activation intervals (i.e., movement cycles characterized by always-ON or always-OFF muscle activation patterns). Further details about the outlier removal process can be found in the study by Rosati *et al* (2017b). The outlier removal process can be performed through the 'remove_add_ints' function as follows:

```
s = CIMAP.remove_add_ints(s)
```

where *s* contains the muscle activation intervals after the outlier removal step.

Muscle activation intervals can be graphically represented using the 'act_plot' function. In the following, the 'act_plot' function is called to represent all the muscle activation intervals of the left and right Lateral Gastrocnemius muscles (LGS_L and LGS_R, respectively):

```
CIMAP.act_plot(s,target = `LGS')
```

where *s* represents the data structure containing the pre-processed muscle activation intervals and target is a variable containing the labels of the muscles to be represented.

Figure 2 shows the output of the 'act_plot' function considering data from the sample dataset included in the toolbox. More specifically, it represents the muscle activation intervals obtained from the left and right LGS muscles of a healthy volunteer during a 5 minute overground walking. Each horizontal blue line represents a muscle activation interval extracted from a single gait cycle expressed in percentage of cycle duration (blue = muscle active, white = muscle inactive). It can be observed that, despite intra-cycle variability, LGS muscle activity mainly occurs between 20% and 50% of the gait cycle for both the left and right sides. The muscle activation intervals included in the sample dataset were computed using the LSTM-MAD algorithm proposed by Ghislieri *et al* (2021).

Before clustering, muscle activation intervals are divided into modalities (i.e., movement cycles characterized by the same number of activation intervals occurring within the cycle duration) by using the 'modality_division' function as follows:

```
muscles = CIMAP.modality_division(s,muscles)
```

where *s* contains the muscle activation intervals and muscles represents the data dictionary suitable for the following clustering analysis.

To visualize the modality distribution and to assess the number of movement cycles belonging to each modality, the 'modality_distribution' function can be used as follows:

```
CIMAP.modality_distribution(s,target = `LGS')
```

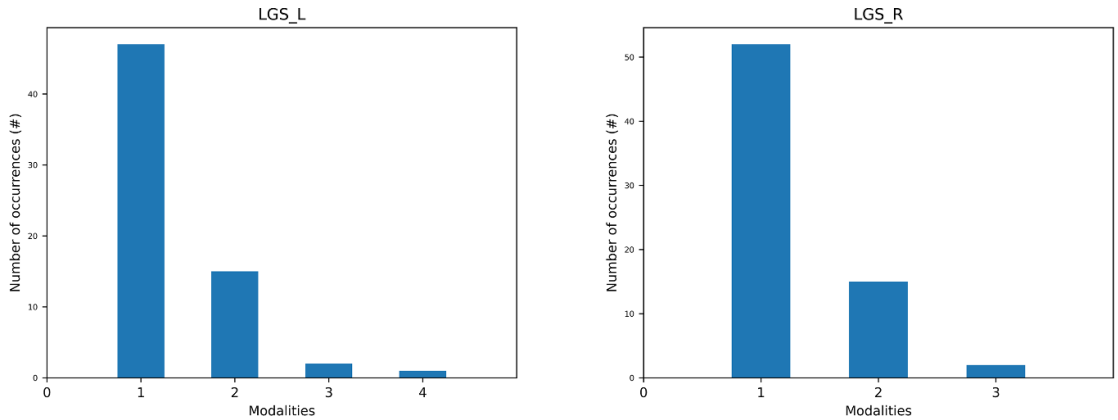

Figure 3. Histograms of movement modalities obtained from the muscle activation intervals of the left and right Lateral Gastrocnemius muscles (LGS_L and LGS_R, respectively) included in the sample dataset. Each histogram represents the number of gait cycles belonging to each modality.

where *s* contains the muscle activation intervals and target is the variable containing the labels of the muscles to be represented.

Figure 3 shows the output of the 'modality_distribution' function representing the histogram of the movement modalities extracted from the muscle activation intervals of the left and right Lateral Gastrocnemius muscles (LGS_L and LGS_R, respectively) included in the sample dataset. In particular, figure 3 shows the number of gait cycles belonging to each modality for both the left and right sides. For example, considering the right side, more than 50 gait cycles are characterized by a single muscle activation (Modality 1), approximately 15 gait cycles are characterized by 2 muscle activations (Modality 2), and less than 5 gait cycles are characterized by 3 muscle activations (Modality 3).

The agglomerative hierarchical clustering is then performed using the 'dendrograms' function, which computes two different dendrograms by using the L_1 norm and L_∞ norm, respectively. To select the optimal cutting point from the two dendrograms (L_1 norm and L_∞ norm), the 'cuts' function is applied to each dendrogram. The optimal cutting point is selected based on the rules defined by (Rosati *et al* 2017b). The clustering analysis can be performed by calling the 'dendrograms' and 'cuts' functions as follows:

```
muscles = CIMAP.dendrograms(muscles)
muscles = CIMAP.cuts(muscles).
```

The 'dendrograms' and 'cuts' functions can be easily customized by users to meet specific data and protocol needs. The toolbox documentation available on GitHub (https://github.com/Biolab-PoliTO/CIMAP) includes further details on the 'dendrograms' and 'cuts' functions.

Clustering results can be graphically represented through the 'dendro_plot' function as follows:

```
CIMAP.dendro_plot(muscles,target = `LGS')
```

where muscles contains the clustering results obtained through the 'dendrograms' and 'cuts' functions and target is the variable containing the labels of the muscles to be represented.

Figure 4 represents the output of the 'dendro_plot' function. For each movement modality, the computed dendrograms are represented. Above each dendrogram, the specific metric and cutting point used are represented, as defined by Rosati *et al* (2017b). The clusters identified after the cutting point selection are represented in different colors.

To save the CIMAP output, the 'algorithm_output' and 'result_saver' functions can be called as follows:

```
cimap_output = CIMAP.algorithm_output(s,muscles)
CIMAP.result_saver(cimap_output)
```

where cimap_output is a data dictionary containing the clustering results of each muscle after discarding non-significant modalities.

CIMAP results are saved in an easy-to-read and open-source format (*.csv*). More specifically, results are in a $M \times (C+1)$ matrix, where M represents the number of muscles and C the total number of cycles. Notice that the first column should contain the labels of each muscle as defined in the input file.

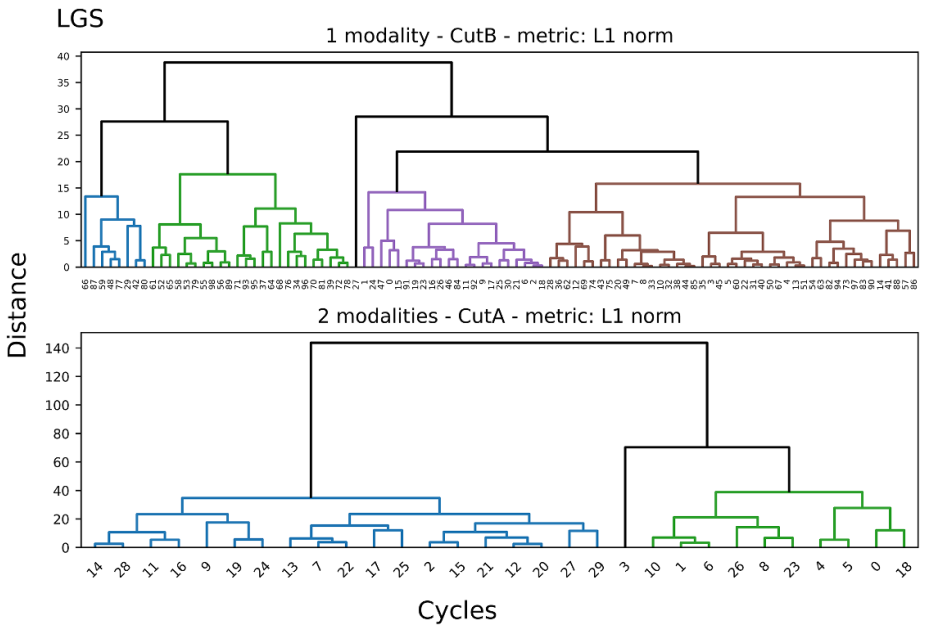

Figure 4. Agglomerative hierarchical clustering dendrograms of the sEMG activation intervals displaying a single modality (at the top) and two modalities (at the bottom). SEMG activation intervals that belong to the same cluster are represented with the same color. Both dendrograms were created using the L_1 norm as the distance metric.

Finally, the sEMG activation intervals clustering computed through CIMAP can be represented using the 'cluster_plot' function as follows:

```
CIMAP.clusters_plot(cimap_output,target = `LGS', color = True)
```

where cimap_output is a data dictionary containing the clustering results and target is the variable containing the labels of the muscles to be represented. The toolbox documentation freely available on GitHub (https://github.com/Biolab-PoliTO/CIMAP) includes further details on the 'cluster_plot' function.

Figure 5 shows the clustering of the sEMG activation intervals computed through CIMAP. The sEMG activation intervals are color-coded according to the colors used in the agglomerative hierarchical clustering dendrograms (figure 4). In each row, the colored lines depict the sEMG activation intervals within a gait cycle. The sEMG activation intervals are grouped into clusters, indicated by different colors. The black lines represent the cluster centroids. Gait cycles belonging to non-representative modalities (i.e., characterized by a small number of gait cycles) are represented in the 'Modality under $Th = 10$' panel.

4. Discussion and conclusions

CIMAP is an open-source and comprehensive toolbox for the assessment of muscle activation patterns from surface electromyographic (sEMG) data. The proposed toolbox offers a complete analysis framework for enhancing the assessment of muscle activation patterns from pre-processing of muscle activation intervals to the representation of agglomerative hierarchical clustering dendrograms. CIMAP adopts an object-oriented programming approach allowing scientists of any programming skill level to easily extend and customize the toolbox to meet specific data and protocol needs. To better explain the toolbox and offer practical guidance, an example of CIMAP application was presented. This example involved analyzing a sample dataset of sEMG signals acquired from a lower-limb muscle of a healthy subject during a 5 min walk.

CIMAP requires as input the muscle activation intervals extracted from the sEMG data of the muscles of a subject. However, this toolbox does not include a muscle activation interval detection step. Therefore, researchers who want to analyze muscle activation patterns using CIMAP should first apply a muscle activity detector before using this toolbox. In the last years, several muscle activity detectors have been proposed, spanning from approaches based on single- (Hodges and Bui 1996, Solnik *et al* 2008) or double-threshold (Bonato *et al* 1998) to more complex approaches based on machine- (Di Nardo *et al* 2022) or deep-learning techniques (Ghislieri *et al* 2021). In particular, muscle activation intervals included in the sample dataset were computed using the LSTM-MAD algorithm proposed by Ghislieri *et al* (2021).

It is well known that muscle activations are characterized by high cycle-to-cycle variability that may strongly reduce the interpretability of the results. In this perspective, CIMAP represents a first resource to be

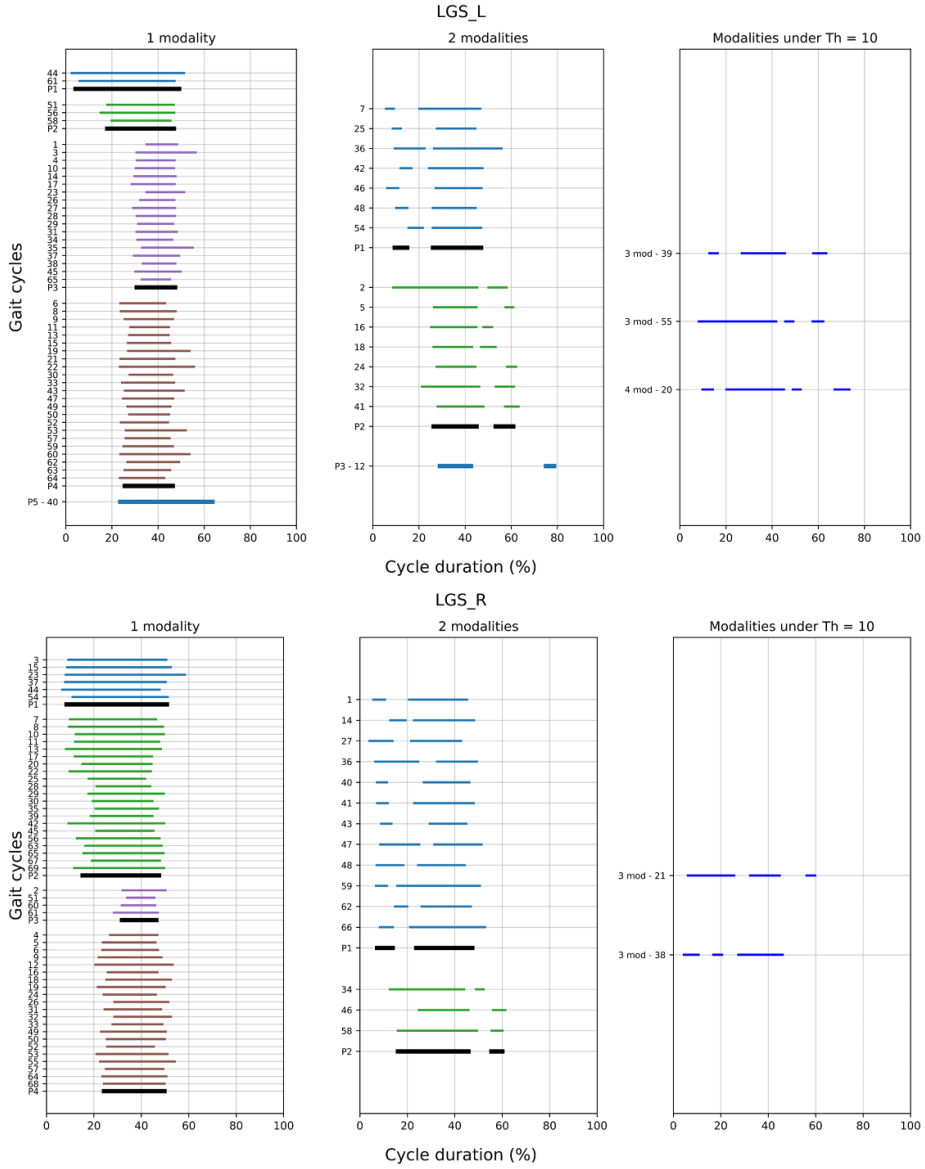

Figure 5. Example of clustering of sEMG activation intervals (muscles: left and right lateral gastrocnemius) computed by means of CIMAP. In each row, the colored lines represent the sEMG activation intervals within a gait cycle. SEMG activation intervals are grouped in clusters (represented by different colors) based on CIMAP output. Black lines represent cluster centroids. Gait cycles belonging to non-representative modalities (i.e., characterized by a small number of gait cycles) are represented in the 'Modality under Th = 10′ panel.

used for dealing with variability in muscle activation patterns analysis during cyclical movements. In the last years, CIMAP was validated in clinics considering different kinds of disorders affecting gait (such as orthopedic and neurological diseases). In particular, CIMAP was used by Castagneri *et al* (2019) for the evaluation of gait asymmetry in adults with megaprosthesis of the knee after bone tumor resection, in elderly subjects after total hip arthroplasty, children suffering from hemiplegic cerebral palsy, and in elderly patients affected by idiopathic normal pressure hydrocephalus. Results demonstrated that gait asymmetry, evaluated through CIMAP, consistent with the expected impact of the pathologies on the muscle activation during gait, suggesting the applicability of the method for the objective assessment of asymmetry. Moreover, in the study by Rosati *et al* (2021), CIMAP algorithm allows the definition of two quantitative indexes for the assessment of subject muscle coordination, enabling clinicians to identify muscle activation patterns that significantly deviate from those of a reference population.

Even if the CIMAP toolbox was originally developed for clinical gait analysis, the clustering approach is independent from the set of muscles considered, it can be easily extended to the study of other cyclical movements, and it can be applied to research areas different from clinics and rehabilitation (e.g. ergonomics, robotics, and sports).

From CIMAP outputs, several parameters can be extracted to deeply understand motor control strategies during movement. For example, the size and variability of each representative cluster can be easily extracted to study muscle activation pattern consistency of a subject muscle over the task duration. During walking tasks, healthy subjects are characterized by an increased cluster size (i.e., gait cycles are described by the same number of muscle activation intervals within the gait cycle duration) and a reduced within-cluster variability (i.e., gait cycles are characterized by similar onset and offset timings within gait cycle duration) compared to pathological conditions. Thus, these parameters can be used to distinguish between physiological and pathological gait conditions.

Notice that the set of input parameters implemented in the CIMAP toolbox was tested and optimized for clinical gait analysis. In case of different tasks or different numbers of movement repetitions, we recommend testing the method and (if necessary) tuning the input parameters. In particular, the input parameters that may require a tuning step are: (*i*) the threshold *Th* used to define representative modalities, (*ii*) the minimum number of elements required to define a significant cluster, and (*iii*) the distance metric used for the agglomerative hierarchical clustering.

One of the limitations of this toolbox is the absence of a dedicated Graphical User Interface (GUI). Although a GUI could improve accessibility, custom code may be needed to adapt the assessment of muscle activation intervals for different movements and datasets, which could be challenging to implement in a GUI. However, the CIMAP toolbox includes several visualization functions that enable researchers to easily track each processing step. Another limitation of the toolbox is the absence of a muscle activation interval detection step. Nevertheless, the main goal of the toolbox is to offer scientists a standardized method for analyzing muscle activation patterns. This allows researchers the possibility to extract muscle activation intervals based on the specific requirements of their dataset.

In conclusion, an open-source Python toolbox for the assessment of muscle activation intervals was presented to help scientists to easily interpret muscle activation patterns during cyclical movements. This approach might provide a step forward to the understanding of motor control strategies from muscle activation intervals in different pathological conditions affecting movement.

Data availability statement

The data that support the findings of this study are openly available at the following URL: https://github.com/Biolab-PoliTO/CIMAP.

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CRediT authorship contribution statement

Gregorio Dotti: Data curation, Methodology, Software, Visualization, Writing—original draft, Writing—review & editing; **Marco Ghislieri**: Data curation, Methodology, Software, Visualization, Writing—original draft, Writing—review & editing; **Cristina Castagneri**: Methodology, Writing—review & editing; **Valentina Agostini**: Conceptualization, Methodology, Writing—review & editing; **Marco Knaflitz**: Conceptualization, Writing—review & editing; **Gabriella Balestra**: Conceptualization, Methodology, Writing—review & editing; **Samanta Rosati**: Conceptualization, Methodology, Writing—review & editing, Supervision.

All the authors have read and agreed to the published version of the manuscript.

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