

PhysioLab - a multivariate physiological computing toolbox for ECG, EMG and EDA signals: a case of study of cardiorespiratory fitness assessment in the elderly population

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Abstract The exponential increase of wearable health-tracking technologies offers new possibilities but also poses new challenges in signal processing to enable fitness monitoring through multimodal physiological recordings. Although there are several software tools used for post-processing in physiological computing applications, limitations in the analysis, incorporating signals from multiple sources, integrating contextual information and providing information visualization tools prevent a widespread use of this technology. To address these issues, we introduce PhysioLab, a multimodal processing Matlab tool for the data analysis of Electromyography (EMG), Electrocardiography (ECG) and Electrodermal Activity (EDA). The software is intended to facilitate the processing and comprehension of multimodal physiological data with the aim of assessing fitness in several domains. A unique feature of PhysioLab is that is informed by normative data grouped by age and sex, allowing contextualization of data based on users' demographics. Besides signal processing, PhysioLab includes a novel approach to multivariable data visualization with the aim of simplifying interpretation by non-experts users. The system

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computes a set of ECG features based on heart rate variability analysis, EMG parameters to quantify force and fatigue levels, and galvanic skin level/responses from EDA signals. Furthermore, PhysioLab provides compatibility with data from multiple low-cost wearable sensors. We conducted an experiment with 17 community-dwelling older adults (64.5 ± 6.4) to assess the feasibility of the tool in characterizing cardiorespiratory profiles during physical activity. Correlation analyses and regression models showed significant interactions between physiology and fitness evaluations. Our results suggest novel ways that physiological parameters could be effectively used to complement traditional fitness assessment.

Keywords Physiological computing · Electrocardiography · Electromyography · Electrodermal activity · Cardiorespiratory fitness · Elderly

1 Introduction

Cardiorespiratory fitness (CRF) is a direct measure of the heart's efficiency during physical activity. For most populations, CRF is probably the most important component in a physical fitness program and exercise prescription [22] because it is a reliable indicator of functional state of respiratory, cardiovascular and muscular systems. CRF can be assessed with maximal or submaximal exercise tests, either by direct assessment of oxygen consumption ($VO_{2\max}$) or through estimation. Maximal exercise tests are protocols that assess cardiorespiratory capacity, which normally use treadmill walking, running or stationary cycling protocols [58]. During these tests, users are continuously monitored via multi-lead ECG (electrocardiography) and, when possible, oxygen consumption equipment. In these tests, users are asked to perform the exercise to exhaustion while specific cardiorespiratory responses are tracked. Instead, submaximal exercise tests typically target some predetermined heart rate (HR) intensity. During these tests, professionals monitor HR and other physiological parameters while users usually perform exercises such as bench stepping, treadmill and cycle ergometers [22]. Finally, field tests are useful for measuring CRF of large groups in a field context. They are characterized for being inexpensive, practical, less time-consuming and more suitable for a personal training setting. Disadvantages of field tests include less accuracy, maximum measures are estimated (instead of directly measured) and limitations to prescribe exercise [58]. In this last approach, CRF levels are generally assessed in older adults through a field test called 6 min walk test or 2 min step test (from The Senior Fitness Test Battery) [40]. Although these are widely used by health professionals [40], their use as a single measurement of the cardiorespiratory status of an individual is intrinsically problematic. For instance, there are several factors which can increase or decrease the scoring for the 6 min walking test or 2 min step test: height, gender, older age, motivation, body weight, medication used before testing, previous test performance, cardiovascular diseases and so on [45]. Consequently, a wide heterogeneity has been observed in the responsiveness of CRF to physical exercise [21]. Since most of the causal factors for the variability cannot be easily addressed, CRF assessments for elderly must be highly sensitive and accurate, particularly for subjects susceptible to a poor training response. Beyond this, there is another issue related with the implementation of some of the CRF tests: the need of very strict controlled situations to implement the tests and the mandatory presence of health professionals to support the assessments.

One methodology used to provide a more precise assessment of CRF in field tests is including multiple physiological measurements such as HR or heart rate variability (HRV) [28]. HRV is extracted from ECG and quantifies the cardiac interaction between sympathetic and

parasympathetic activity, both branches of the autonomic nervous system (ANS) [14]. During the last few decades, the study of HRV as a method for assessing ANS activity in several diseases and conditions has greatly increased [19, 53]. HRV is a powerful marker of cardiac autonomic control, flexibility and regulation. Time and frequency domain measurements of HRV constitute a non-invasive method to evaluate parasympathetic tone and sympathovagal balance, which have a high value to prognosticate cardiovascular risks [14]. Recent studies suggest that regular physical exercise has strong benefits in HRV modulation [25]. This association establishes new opportunities to include HRV parameters for improving the physiological characterization of cardiorespiratory profiles in populations such as older adults. Particularly, the notable rise of wearable and low-cost personal tracking technologies has increased the interest to study the relationship between HRV and exercise practices [41]. However, the inherent difficulty to process ECG data, to extract, and to interpret HRV parameters creates a significant gap between technology and information exploitation. Although HR methods to assess and prescribe exercise are well-known [22], both software and hardware tools to carry out this analysis are usually expensive, limited or too generic, thus constraining an extensive use of HR parameters for complementing CRF. Particularly, multiple software tools for HRV analysis include time, frequency and geometric methods to extract several of the most widely used parameters [44]. Nevertheless, the lack of integration of context-related information in physiological computing software tools often prevents its widespread use by expert users. Furthermore, the visualization of HRV parameters is mainly tabular or in the form of stacked plots, which restricts HRV data comprehension and interpretation by non-expert users [49]. Novel visualization methods of HRV data may provide a better understanding and appropriation of CRF meaning in different physical activity contexts. Thus, advances in novel software tools with different visualization methods for HRV parameters may increase drastically the usability of wearable HR activity trackers and software applications, providing an empowerment in the use of their data.

1.1 Multimodal physiological toolboxes

In this section, we review the available toolboxes for multimodal physiological signal processing. Interestingly, we found a list of 7 different software tools available to the community which can be used to process data from several physiological signals (see Table 1). Three of the toolboxes are mainly used with their respective hardware kits and have a business model. Firstly, the Acqknowledge [4] provides support for processing a wide range of physiological signals such as electroencephalography (EEG), electromyography (EMG), electrodermal activity (EDA), electrooculography (EOG), electroglottographic (EGG) and ECG. The toolbox is offered in combination with the BIOPAC biosignal devices and performs tasks from data acquisition to modelling using a simplistic guide user interface (GUI) with menus and dialogs. Similarly, the g.BSanalyze [36] is a software tool which can perform offline biosignal data analysis under the Matlab environment or standalone. This software has been extensively used for the brain computer interface (BCI) community in conjunction with the EEG hardware produced in the same company. The toolbox integrates specialized functions to visualize neurophysiological signals and includes many biosignal datasets of multiple BCI paradigms. The last software with paid license is the OpenSignals [10] which uses data processing modules as optional add-ons of a free signal visualization core tool. The core functionality embraces data acquisition and data visualization and the add-ons are for HRV and EMG data analysis. Similarly, the ANSLAB uses a mix-model to commercialize a software created to carry out research in psychophysiology comprising ECG, EMG, EDA, PPG and other cardiorespiratory signals [57]. Two software tools that do not include GUIs are the Biosig Project [52] and the TEAP (Toolbox for Emotional feature extraction from

Table 1 Relevant multimodal physiological toolboxes for signal post-processing and visualization

Software tools	Signals supported	Scope	First release date	GUI	License	Studies	Functionality
Acqknowledge [4]	ECG, EDA, EEG, EGG, EMG and EOG	General Purposes	1993	Yes	Paid	> 10	Data acquisition, signal filtering, artifact processing, feature extraction, classification and modelling
g.BSanalyze [36]	EEG, ECG	General Purposes	2004	Yes	Paid	> 10	Data acquisition, signal filtering, artifact processing, feature extraction, visualization.
OpenSignals [10]	EMG, EDA, Resp	Biosignal visualization	2012	Yes	Paid (as plugins)	< 5	Data acquisition, Signal visualization, feature extraction
ANSLAB [57]	ECG, EMG, EDA, PPG, ICG, Resp	General Purposes	2004	Yes	Mix Model	< 5	Feature extraction, classification
BioSig Project [52]	EEG, ECoG, ECG, EOG, EMG, Resp	General Purposes	2003	No	Open Source	> 10	Data acquisition, signal filtering, artifact processing, feature extraction, classification, modeling, visualization.
TEAP [46]	EEG, ECG, EDA	Affective computing	2017	No	Open Source	--	Feature extraction, visualization
Augsburg Biosignal toolbox (AuBT) [54]	EDA, EMG, ECG, Resp	Emotion Recognition	2006	Yes	Open Source	< 5	Feature extraction, feature selection, classification
Physiolab	EMG, ECG, EDA	Fitness Assessment	2016	Yes	Open Source	< 5	Signal filtering, artifact processing, feature extraction, visualization, data interpretation

EEG Electrocardiography, *EDA* Electrodermal Activity, *EEG* Electroencephalography, *EMG* Electromyography, *EOG* Electrooculography, *Resp* Respiration, *ICG* Impedance Cardiography, *ECoG* ElectroCorticography

Physiological signals) [46]. The first incorporates a large list of open source libraries wrote in C, C++, Matlab and Octave and methods for signal processing, feature extraction and classification and the TEAP is a toolbox oriented for affective computing applications covering analysis for EEG, ECG and EDA signals. Finally, the Augsburg Biosignal Toolbox [54] comes along with a GUI which facilitates the processing of multiple physiological signals for extracting features, automatically select the most relevant ones and use them to train classifiers.

Based in the comparison presented in Table 1 and some of the limitations offered by the state-of-the-art toolboxes such as the cost associated with licensing, the generality of the scope (which limits the specificity of their signal processing methods), the lack of graphical interfaces for their operability and the absence of techniques to facilitate data interpretation, we developed PhysioLab, a multimodal physiological computing toolbox. The software reported here includes three main features: a) the integration of multiple physiological signals such as ECG, EMG and EDA which can be processed, examined and compared for a more comprehensive and inclusive analysis; b) the flexibility provided by PhysioLab to carry out both long-term and short-term physical behavior monitoring through an analysis of physiological parameters; and c) the inclusion of a novel visualization of CRF parameters, facilitating the presentation and interpretation of results. The inclusion of EDA and EMG signal processing methods allows to extend the use of PhysioLab beyond the CRF domain, opening new possibilities to integrate the analysis of physiological signals for musculoskeletal fitness and mental wellbeing.

The goal of this paper is two-fold: (1) to describe PhysioLab as a multimodal Matlab tool for physiological signal processing and data analysis, and (2) to demonstrate its potential through a field study of CRF assessment of an older population. To that end, ECG signals from 17 healthy older adults were collected during a physical activity intervention. A multilinear regression model approach was used to create a set of linear equations, which describe users in various fitness domains (such as balance and cardiorespiratory) through physiological parameters extracted from PhysioLab.

2 Methodology

2.1 PhysioLab: Multivariate physiological computing toolbox

PhysioLab v.1.0 is a physiological computing toolbox developed to support the analysis of ECG, EMG and EDA signals, and facilitate data interpretation with a focus in the fitness domain. The toolbox integrates multiple widely used algorithms with normative data for signal pre-processing and feature extraction, and includes a novel multivariate visualization method for data interpretation for end-users. PhysioLab has been developed using Matlab release 2013a (MathWorks Inc., Massachusetts, US). The toolbox is freely available at: <http://neurorehabilitation.m-iti.org/tools/physiolab>

2.1.1 Input data and compatibility

PhysioLab can import data files from different low-cost physiological sensors such as Bitalino,¹ Biosignal-Plux,² e-Health Kit³ or Myo Armband,⁴ exported from their native

¹ <http://www.bitalino.com/>

² <http://biosignalsplux.com>

³ <https://www.cooking-hacks.com/health-sensors-complete-kit-biometric-medical-arduino-raspberry-pi>

⁴ <https://www.myo.com/>

software packages [35, 37]. Further, to allow the easy integration with other technologies, a “Load from Workspace” option enables loading any physiological data available from the Matlab Workspace organized as column vectors. This option is extremely useful if a user wants to manually pre-process the data or extend the analysis with methods not included in PhysioLab. Additionally, the software provides the option to select a specific time-based Region of Interest (ROI) from the signals. Finally, using the option “Save in Workspace” the user can export the processed data from PhysioLab and make it available to the user in the Matlab workspace for further analysis.

2.1.2 User Interface

PhysioLab is fully operated using a graphical user interface, which is divided into three parts: a) Analysis Panel, b) Signal Visualization Panel, and c) Feature Extraction Panel (see Fig. 1).

- a. **Analysis Panel:** this panel includes the three physiological signals supported at this stage by PhysioLab: EMG, ECG and EDA. The signal to be depicted in the GUI should be selected. In this panel, users can customize some parameters used for the analysis in order to adjust the algorithms, thus improving the accuracy of feature extraction. For EMG signals, time and frequency domains are included. ECG signal analysis is based on R-peak

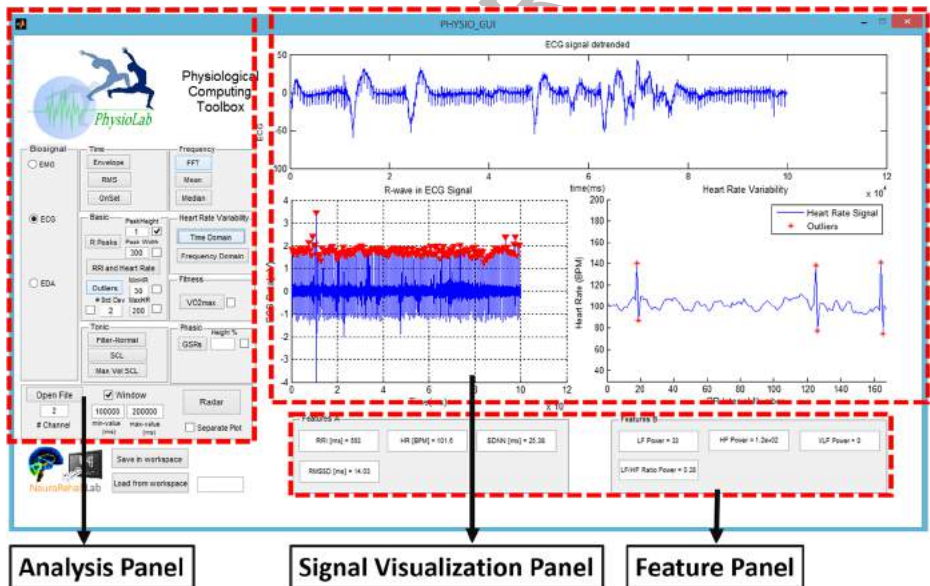


Fig. 1 The graphical user interface of PhysioLab is divided in three parts: 1) Analysis Panel, 2) Signal Visualization and 3) Feature Extraction panel. In the Analysis Panel, users can choose the Biosignal (EMG, ECG or EDA); the EMG analysis includes Time (Envelope, RMS and OnSet) and Frequency (FFT, Mean, Median) domain parameters. The ECG covers basic (R-peak, RRI and HR computation, and Outliers detection) as well as HRV analysis (Time and Frequency Domains). Finally, EDA analysis embraces Tonic (Filter and Normalizes the signal, compute SCL and its Max. Vel) and Phasic (GSRs detection). The Signal Visualization Panel includes three windows to see the raw data (top), the first category of the processed data (lower-left) and the second category of the same (lower-right). Finally, the Feature Panel prints the Features A (e.g. time domain, tonic) and Features B (e.g. frequency, phasic) in small boxes at the lower right corner of the GUI

detection. The analysis includes HR, HRV variables (in the time and frequency domains) and the estimation of VO_{2max} . EDA signals are processed and divided into tonic and phasic components, representing the slow and fast behavior of the skin conductance. This panel also includes an option to personalize the range of the data to be analyzed by predefining signal windows or ROIs before starting the analysis.

- b. **Signal Visualization Panel:** this section contains multiple representations of the processed signal to dynamically visualize the processing results and adjust the analysis. The signal to be depicted in this panel is selected in the analysis panel. Particularly, the top window displays the raw data and the lower-left window plots the first category of processing (time for EMG, R-Peak analysis for ECG, and tonic responses for EDA). Similarly, second category features (frequency for EMG, HRV for ECG, and phasic responses for EDA) are displayed in the lower-right panel to complement and ease the comparison between categories. The extracted features such as ECG waveform and detected R-Peaks, linear EMG envelope and normalized EDA signals are plotted superimposed with the processed data to facilitate visual inspection of the results. Additionally, by selecting the “Separate Plot” option, plots can be created in separate pop-up windows facilitating the data visualization. Finally, we created a radar plot (see Fig. 7) intended to simplify fitness assessment through a clear and color-coded representation of the physiological parameters using a multivariate visualization [34]. For the generation of the radar plots we rely on normative data to generate three fitness zones or profiles (low-normal-high) in which to categorize users. Each axis of the radar is normalized considering the min and max values of each parameter (see Table 2), therefore avoiding the misinterpretation of the area inside of the radar. User’s extracted physiological features are plotted in a way that can be directly compared with normative data in order to facilitate the interpretation of the user performance (see [34] for further information on the Radar-Plot). PhysioLab includes a radar plotting menu which allows a previous configuration of the visualization parameters, including age, gender and type of recording (short or long term). Then, the user can choose 5 out of 7 physiological variables to create the radar plot with the normative data. Moreover, this normative data is uploaded from an excel datasheet which can be modified by the researcher, thus enabling users including novel and specific normative data to create the fitness zones. The radar plotting menu is accessed using the option Radar from the Analysis Panel. Currently, PhysioLab includes only radar plots to assist the data interpretation specifically in the CRF domain, but the concept can be extended to other fitness domains using multiple physiological signals and features.
- c. **Feature Panel:** the bottom panel contains a number of divisions to display the values of the features extracted from each signal using the international system of units. As in the previous panel, left and right side boxes display first and second category of features, respectively.

2.1.3 Feature extraction

Electromyography (EMG) PhysioLab supports the analysis of the EMG data and its processing in time and frequency domains. In physiological recordings, the presence of trends - slow and gradual changes in some properties over whole recordings - are common. Hence, the EMG signals are initially detrended by subtracting a moving average. This technique is

Table 2 Summary of the time domain ECG (R-Peak) parameters calculated by PhysioLab software with the normative values found in past researches

Variable [units]	Definition	Meaning and Findings	Population	Normative values for adults
mRRR [ms]	The mean of RR intervals	For resting recordings, the smaller the mean RRR is, the more nervous a person is.	Healthy Adults	Short term [53] 903 ± 109
SDNN [ms]	Standard deviation of all RR intervals	Low values (< 50 ms) are associated with low ejection fraction, poor exercise performance [29] and increases in risk for death after myocardial infarction [47]. The higher the SDNN is, the higher a person's emotion variability is.	Healthy and Non-Healthy Older Adults	Long term [31] 141.0 ± 36.0 Short term [53] 36.9 ± 13.8
RMSSD [ms]	The square root of the mean of the sum of the squares of differences between adjacent RR intervals	Reflects the modulation of cardiac parasympathetic activity [20].	Healthy Young Adults	Long term [31] 26.0 ± 9.0 Short term [53] 26.3 ± 13.6
VO_{2max} [ml/Kg*min]	Maximum oxygen uptake capacity computed using HR information	Low values reflect a down regulation of the parasympathetic system [42]. Provides an estimation of the cardiorespiratory performance.	Healthy Adults	Men- short term [22] Poor: ≤ 37 , Fair: 38–41, Good: 42–45, Excellent: 46–52 Superior: 53+ Women Short-Term Poor: ≤ 32 Fair: 33–35 Good: 36–38 Excellent: 39–44 Superior: 45+

always desirable to improve reliability of the signal to describe complex physiological phenomena and improve the diagnoses [59]. Subsequently, the signals are full-wave rectified and low-pass filtered following standard recommendations for EMG processing (cutoff frequencies below 20 Hz) [26]. PhysioLab uses 20 Hz by default.

Time Domain Analysis

- The Linear Envelope (LE) is the most popular demodulation technique used to extract the amplitude information from the EMG waveforms [26], and is related to the force-time curve of the recorded muscle. EMG LE and force are assumed to be linear under isometric conditions and non-linear under isotonic conditions [3]. PhysioLab provides a representation of both the pre-processed EMG signal and the linear envelope in the signal visualization panel (see Fig. 2a, b).
- The Root-Mean-Square (RMS) amplitude of the EMG signal is one of the more commonly used EMG nonlinear features, which is computed as follows:

$$RMS = \sqrt{\frac{1}{T} \sum_{t=1}^T EMG^2(t)} \quad (1)$$

Where t_i represents each sampling data point of an EMG signal. The unit of measurement is mV.

The RMS value has two interpretations: *physically* the RMS reflects the mean power, an excellent indicator of the amplitude of the signal [26]; *physiologically*, changes in the RMS values of the EMG signal are good descriptors of motor unit behavior [22]. For example, surface electromyographic recordings showed increased RMS values during the presence of fatigue [8].

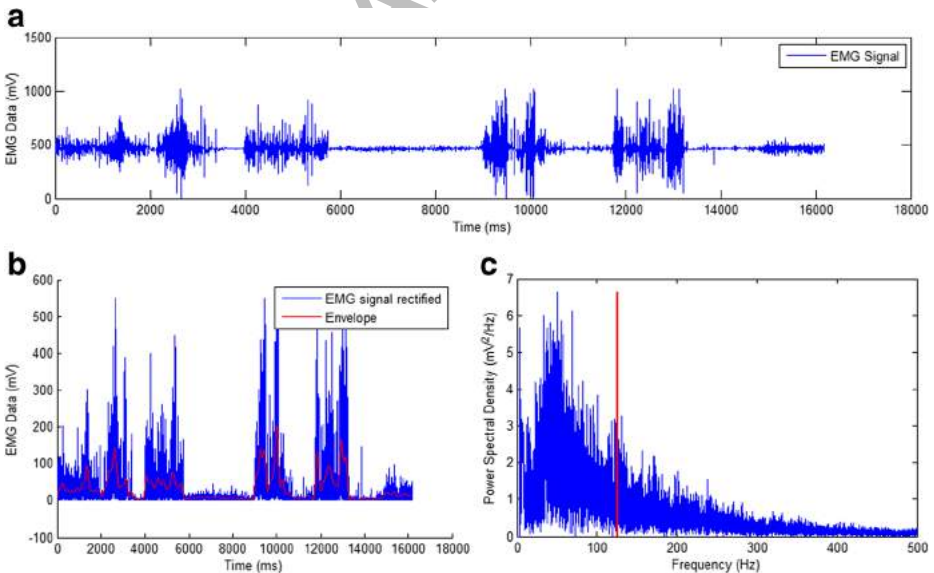


Fig. 2 EMG signal processing steps in PhysioLab. **a** EMG raw data, **b** EMG signal detrended and full-wave rectified (blue) and EMG linear envelope (red) and **c** PSD of EMG signal (blue) and MNF value (red line). Example data are from forearm muscles of a healthy young adult during contractions recorded along 20 s using the Biosignal Plux toolkit (Plux Wireless Biosignals, Lisbon, Portugal)

- In most cases, we want to identify when a muscle is activated, for how long it stays activated, and how much activity there was within the detection period. The Onset determines when the electrical activity of the muscle begins, and the Offset when it terminates. PhysioLab enables two ways to carry out their detection: i) user assisted (for individual detection) and ii) automatic (for multiple automatic detections). In the assisted detection, the user manually chooses 4 points (2 before and 2 after the activation) within the signal to accurately detect the timing of the Onset/Offset. In the case of the automatic method, it involves extracting the baseline parameters of the signal (mean and standard deviation) and then a double threshold is applied. The first threshold determines a minimal activity duration and the second one the minimal EMG amplitude. A double-threshold approach provides a minimization of false detections that often occur prior to muscle contraction using the baseline information. The amplitude values of the EMG Onsets are diverse and they depend of the type of muscle. However, a time window from 10 to 50 ms is used as a second threshold to minimize erratic detections of contractions [26].

Frequency Domain Analysis

EMG frequency analysis can also provide both physiological and non-physiological information of the signal. Specifically, *non-physiological* information reveals the presence of artifacts and noise contamination from different sources such as electrical interference [26]. *Physiologically*, EMG frequency analysis is normally associated with fatigue analysis [8]. A Fast Fourier Transform is used to compute the power spectrum density (PSD), which for normal human muscles with surface EMG is between 20 Hz and 450 Hz [12]. Muscle fatigue alters the spectral information by changing the shape of the action potentials of muscle fibers, decreasing the amplitude and increasing the duration [8]. Hence, as fatigue progresses there is a shift of power towards lower frequencies, which can be quantified using two measurements:

- The Mean Frequency (MNF) [50] is computed as a sum product of the EMG power spectrum and frequency, divided by a total sum of spectrum intensity. MNF is computed as follows:

$$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j} \quad (2)$$

- The Median Frequency (MDF), which is a frequency value at which the EMG power spectrum is divided into two regions with an equal integrated power is computed. MDF is computed as follows:

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j \quad (3)$$

where P_j is the EMG power spectrum at a frequency bin j , M is the length of the frequency bin and f_j is the frequency value at a frequency bin j .

PhysioLab displays MNF features superimposed over the EMG PSD plot (Fig. 2c).

Electrocardiography (ECG) ECG processing in PhysioLab is based mostly on HR time domain features. First, the original ECG signal is fitted with a low order polynomial ($n < 10$), which is then used to detrend it. Some muscle tremors (voluntary or involuntary) are unavoidable [18] and produce EMG activity with amplitudes and frequencies 0.1–1 mV and 5 Hz–1 kHz, respectively, that partly overlap with the ECG signal. This induces in ECG a baseline wander effect that can mask important information. Thus, ECG signal is smoothed by a fifth order Savitzky-Golay FIR filter. To extract HR information, each

heartbeat waveform is analyzed and R-peaks detection is carried out using a threshold based on peak morphology analysis [16]. PhysioLab presents both the original and detrended signals after the R-peak detection, in case the user needs to perform manual adjustments of the thresholds in order to improve the accuracy of the detection. Additionally, the user can also manually adjust the temporal and amplitude thresholds (R-peak's height and width). Once the R-peaks are extracted, the HR can be extracted from the RR information by:

$$HR_{inbeats}/min = 1000/RR \text{ (in ms)} \times 60 \quad (4)$$

PhysioLab computes the average of the HR and prints it in the feature panel.

Heart Rate Variability (HRV)

Having the HR information available, an analysis of heart rate variability (HRV) can also be carried out. HRV analysis assesses the regulation of heart's activity by analyzing the variation over time of the R peaks. Considering the important role of RR interval editing for HRV analysis [2], PhysioLab facilitates a R-to-R peak correction by: a) allowing users to filter HR data between a specific range of HR values (30 to 200 BPM as default); and b) identifying and removing data outliers which are HR values differing from the previous one by more than n -times the standard deviation [33] ($n = 2$ as default) of the complete dataset. RR interval correction is carried out before computing both time and frequency domain parameters.

PhysioLab computes the following time domain HRV parameters:

- **mRRI**: defined as the mean value of normal R-to-R or RR intervals (RRI or NNI).
- **SDNN** (sometimes also called **SDRR**): is the standard deviation of RR intervals and is a global index of HRV associated with cardiac resilience. SDNN also reflects the cyclic components responsible for the HRV in the period of recording. SDNN is computed as follows:

$$SDNN = \sqrt{\frac{1}{N-1} \sum_{n=2}^N [I(n) - \bar{I}]^2} \quad (5)$$

where I is the RR interval and N the total number of RR intervals in the data. Reduced SDNN values (< 50 ms) have been found to be associated with a low ejection fraction (measurement of the percentage of blood leaving the heart each time it contracts) [29], poor exercise performance [9], high limitation in physical activity (New York Heart Association functional classification) [24] and short RR intervals. Furthermore, SDNN has been found to be a risk factor for mortality, with low values being associated with an increased risk for death after myocardial infarction reflecting failure of heart rate in regularization functions during the night [29].

- **RMSSD** (square root of the mean squared differences of successive RR intervals): normally represents the difference between consecutive R waves. The RMSSD is calculated using:

$$RMSSD = \sqrt{\frac{1}{N-2} \sum_{n=3}^N [I(n) - I(n-1)]^2} \quad (6)$$

RMSSD is used to estimate the vagally-mediated changes reflected in HRV. Low values reflect a possible down regulation of the parasympathetic system [42]. Besides, low RMSSD values have been shown to correlate with sudden unexplained death in epilepsy (SUDEP) [55].

PhysioLab also computes the following frequency domain HRV parameters. A Welch's PSD estimation with a Hanning window is used to estimate the HRV spectrum [34].

- **LF** (low-frequency power): represents the power of the periodic oscillations of the heart rate signal between the 0.04 Hz and 0.15 Hz frequencies. LF normally is modulated by both the sympathetic and parasympathetic systems [14]. Increases in LF are often interpreted as a consequence of sympathetic activity such as mental effort and workload [14].
- **HF** (high-frequency power): embraces the PSD between 0.15 Hz and 0.4 Hz. HF is generally mediated by the respiration and it has been used as a marker of vagal modulation (parasympathetic activity) [14].
- **LF/HF**: this ratio has been used to reflect the global sympathico-vagal balance and it is one of the most extensively used HRV markers [14].
- **VLF** (very-low frequency): the VLF component reflects sympathetic activity and is probably a major determinant of physical activity in long-term recordings [7]. VLF includes values between 0.003 Hz and 0.04 Hz.

Cardiorespiratory Fitness Parameters

Finally, another important factor to evaluate functional cardiorespiratory capacity is VO_{2max} . VO_{2max} is the maximum oxygen uptake capacity and it has been shown to be a reliable measure reflecting the functional capacity of the cardiorespiratory system [12]. We estimate VO_{2max} as described in [17], by performing the ratio between the heart rate values at rest (HR_{rest}) and maximal exercise (HR_{max}). The value of HR_{rest} is defined as the lowest value of any 1-min average during a 5-min sampling period, and the HR_{max} is approximated using the highest 5-s average during different exercise tests, like step or treadmill tests [51]. Consequently, PhysioLab computes VO_{2max} using two different ECG signals, during resting and exercising:

$$VO_{2max} = (15.0 \text{ ml} \cdot \text{min}^{-1} \cdot \text{Kg}^{-1}) \times \frac{HR_{max}}{HR_{rest}} \quad (7)$$

Additionally, when ECG data for HR_{max} is missing, PhysioLab approximates it through the widely accepted formula by Tanaka [48], which is an age-dependent model to compute HR_{max} . VO_{2max} is widely used to classify cardiorespiratory fitness performance (poor, fair, good, excellent or superior) using age and gender specific normative Tables [52].

The following table summarizes the physiological meaning of the time domain HRV parameters extracted by PhysioLab for electrocardiography analysis based on short and long-term recording literature.

Table 2 summarizes some of the most important results found in different studies with hundreds of participants regarding the variations of the time domain HRV parameters in short and long term recordings for women and men. These data are used to facilitate the elaboration of the cardiorespiratory radar plots (see Fig. 7).

Electrodermal activity (EDA) The analysis of the EDA signal can be split into tonic and phasic components. The Skin Conductance Level (SCL) or Tonic Level denotes the baseline or resting level of the EDA signal. SCL is known to relate to sweat gland activity [5] and is

measured in microSiemens (μS). Galvanic Skin Responses (GSRs) or Phasic Changes are noticeable episodes of sudden increases of conductance caused by purely sympathetic arousal generally generated by an external stimulus. The level of GSRs is thought to be an accurate indicator of the degree of arousal caused by the stimuli [5].

To eliminate high-frequency noise, an 8th order low-pass filter with a cut-off frequency $f_c = 15$ Hz is applied. This allows the reduction of false positive in the detection of phasic events which do not demand high frequency responses [39, 59]. Then, in order to minimize the impact of overlapping (superimposed) GSRs, we implemented a solution based on deconvolution techniques to decompose EDA into its tonic and phasic components. Subsequently, with the purpose of facilitating the comparison of EDA signals from different users, data are normalized as follows [34]:

$$SCL_{normalized} = \frac{SCL_{now} - SCL_{min}}{SCL_{max} - SCL_{min}} \times 100 \quad (8)$$

GSRs detection is carried out based on a minimal distance between consecutive GSRs (set as 4 s) and a minimal amplitude (in %) threshold provided by the user (default value = 30%) [6]. Based on response latencies to stimuli, it is common to use a 1–4 s latency window. Hence, any GSR that begins between 1 and 4 s following stimulus onset is generally considered to be elicited by that stimulus [11]. GSRs that are not elicited by a stimulus are referred to as a spontaneous or nonspecific GSR (NS-GSRs). PhysioLab presents the different steps of the EDA feature extraction process in the signal visualization panel: raw data, filtered and normalized EDA data, and superimposed GSR detection with temporal labels (see Fig. 3). Additionally, the mean value of SCL and max value of SCL velocity are extracted and displayed in the Features Panel, jointly with the SCL curve, superimposed to the raw data plot.

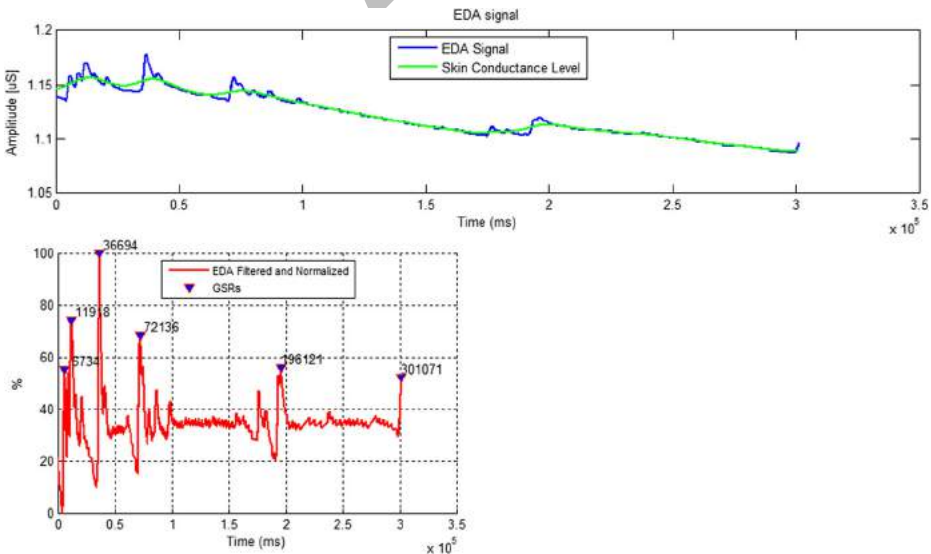


Fig. 3 EDA processing done by PhysioLab represented in the signal visualization panel. At the top, raw data and SCL superimposed. At the lower-left, EDA signal normalized and GSRs detected and labeled in time. Example data recorded from middle phalanges of a healthy young adult during resting recorded along five minutes using the Biosignal Plux toolkit (Plux Wireless Biosignals, Lisbon, Portugal)

2.2 Pilot study: Complementing CRF assessment through PhysioLab

To evaluate the usefulness of PhysioLab to process physiological signals, extract relevant features and visualize data in CRF domain, we carried out a study with older adults. Then, the study depicts the very first effort to assess the feasibility of PhysioLab to complement CRF assessment through physiological signals (ECG in this case) rather than explore the usability issues of the software with health professionals.

2.2.1 Fitness assessment

A set of standard senior fitness tests and assessment measures were used to characterize users in multiple fitness domains, namely:

- The 2 min step test (ST) was used as an aerobic endurance test. The ST is a simple way to assess cardiorespiratory fitness in older adults by counting the number of knee liftings during 2 min [29].
- The 30-s chair stand test (CST) assesses lower-body strength by counting the number of full stands from a seated position that can be completed in 30 s. CST is considered essential for detecting early decline in functional independence [22].
- The Unipedal stance test (with open-UPST_{open} and closed-UPST_{closed} eyes) provides a simple measure of static balance performance. The test counts the number of seconds the user is able to stay balanced on the dominant leg up to 45 s [29].
- The 8 ft Up and Go Test (FUG) is a coordination and agility test that measures reaction times for standing and walking from a sitting position [40].
- The Composite Physical Function scale (CPF) assesses physical independence through questions about the user's ability to perform indoor (for example, bathing) and outdoor (for example, hiking or gardening) daily life activities [40].
- The Modified Baecke Questionnaire (MBQ) measures frequent physical activity in the elderly on a 4-level rating of household, sport and leisure activities. The MBQ is frequently used to classify individuals as displaying low, moderate or active daily physical activity [38].
- The Short-Form 36 Healthy Survey (SF36) evaluates health status and quality-of-life by examining a person's perceived limitations in physical functioning and mental health. The physical domain includes activities of daily living related with Physical Functioning, Role Physical, Bodily Pain, and General Health. The Mental domain includes Social Functioning, general Mental Health, covering psychological distress and well-being, Emotional Role Functioning and Vitality [56].
- The Mini-Mental State Examination (MMSE) is a screening tool to assess cognitive impairment [30]. The MMSE addresses orientation, registration, attention and calculation, recall, language and praxis.

2.2.2 Participants

Seventeen healthy older adult participants (14 women, age 64.5 ± 6.4 years, height 1.57 ± 0.67 m and mass 69.1 ± 12.2 kg.) were recruited in a local senior fitness center (see Table 3). All participants had no recent injuries in upper/lower limbs, were able to stand up without any support and had no neurological conditions that prevented the execution and understanding of the experiment. Finally, all participants signed an informed consent form before start.

Table 3 Characterization of participants

Characteristic/Assessment test	Values \pm SD (Range)
Age (years old)	64.5 \pm 6.4 (53–76)
BMI (Kg/m ²)	27.9 \pm 4.7 (19.7–38.7)
Resting HR (bpm)	76.0 \pm 12.1 (60–97)
HR _{max}	163.2 \pm 4.3 (154–170)
VO _{2max}	33.0 \pm 4.4 (25–39)
METs	6.47 \pm 0.47 (3.8–9.5)
ST	97 \pm 18 (60–136)
CST	18 \pm 2 (15–25)
UPST _{open}	26.1 \pm 14.3 (3.0–45.0)
UPST _{closed}	5.8 \pm 7.4 (1.1–31.6)
FUG	4.6 \pm 0.6 (3.6–5.8)
CPF	22 \pm 2 (18–24)
MBQ	12.1 \pm 6.1 (5.4–22.3)
SF36	627.0 \pm 117.0 (410.1–774.0)
MMSE	28 \pm 2 (24–30)

Values represent mean \pm SD (range). BMI stands for body mass index; bpm for beats per minute, HR for heart rate, HRmax for maximum heart rate

2.2.3 Protocol and data collection

Physiological data were collected from the participants during a minimally controlled interactive experience using an exercise videogame (Exergame) of moderate intensity, in which participants behaved freely playing a Kinect based computer game. The total experience's length was around 30 min. ECG signals were recorded during a period of resting (before the interaction) and during the activity.

ECG data were recorded using the BioSignal Plux toolkit, a wearable body sensing platform (Plux Wireless Biosignals, Lisbon, Portugal) using a surface-mounted triode dry electrode with standard 2 cm spacing of silver chloride electrodes placed on the V₂ pre-cordial derivation. Raw sensor data were acquired with a 1000 Hz sampling rate. The wearable system was connected to a computer through a Bluetooth transmitter placed on the left forearm.

The senior fitness tests were administered and scored by a professional sport scientist three weeks before the intervention. Both fitness assessment and the Exergame interaction took place in a conventional exercising room on a local senior fitness center.

2.2.4 Data analysis

Physiology Seven parameters were extracted from the ECG data using PhysioLab: HR_{resting}, HR_{difference} (HR during exercise – HR_{resting}), HR_{max} (computed using Tanaka's formula, 208-(0.7*Age)), VO_{2max}, SDNN and RMSSD. Additionally, Energy Expenditure (EE) was directly computed using HR data through the equation of EE (KJ*min⁻¹) developed by Keytel et al. [27].

$$EE = -59.39 + gender \times (-36.37 + 0.27 \times age + 0.39 \times weight + 0.40 \times VO_{2max} + 0.63 \times HR) + (1 - gender) \times (0.27 \times age + 0.10 \times weight + 0.980 \times VO_{2max} + 0.45 \times HR) \quad (9)$$

The Metabolic Equivalents (METs), which use as reference the resting metabolic state, was computed assuming one MET equals the resting oxygen uptake (which is approximately

3.5 mL/Kg/min). EE was converted to METs dividing the value by resting energy expenditure [23]. In this way, physical activity can be classified as light (< 3 METs), moderate (3 to 6 METs) and vigorous (> 6 METs) [13].

Finally, a collinearity analysis of the seven parameters was carried out using Principal Components Analysis (PCA) in order to identify redundancy among extracted features. PCA generates a new set of mutually orthogonal variables (principal components) via making linear combinations of the originals. By plotting multiple principal components in the same space, we can develop a deeper understanding of the driving forces present in the data [33]. Thus, redundant information will appear in the plot with a similar orientation, revealing poor orthogonality.

The normality of data was assessed using a Kolmogorov-Smirnov test. A correlation analysis was used to explore interactions between the senior fitness tests scores and the selected set physiological parameters. All the statistical tests were performed using Matlab v.2013a.

Data regarding fitness assessment Data from the fitness assessment were normalized to one considering the maximum values for each score to facilitate the clustering process, and were divided and grouped in five fitness domains according to the subcomponents that they assess:

- Cognitive Functioning and Mental Health (Mental): data from MMSE and the mental domain of SF36 were normalized to 1 and averaged together.
- Activities of Daily Living (ADL): assessed as the normalized and averaged values of the CPF scale, MBQ and physical section of SF36.
- Balance: assessed by both unipedal stance tests (eyes open and closed) and the FUG test.
- Cardiorespiratory: assessed by the ST.
- Musculoskeletal: assessed by the CST.

A multilinear regression approach was implemented (see section 3.3) in order to determine linear equations using physiological parameters such as predictors and fitness domains as responses. The significance level for the multilinear modelling approach was considered 0.05.

Finally, we present a scheme (Fig. 4) describing the entire process carried out for data collection, physiological signal processing and statistical analysis:

3 Results

3.1 CRF data visualization and interpretation

Although instruments such as ST, CPF, SF36 or CST are considered valid and reliable descriptors of fitness status in the older adult population [22], many of these assess multiple domains of fitness simultaneously, the interpretation of the scores relies on a comparison with normative data, and are prone to human error. Thus, the interpretation of these data is difficult. To validate our novel multimodal visualization approach, we divided the participants in the higher and lower 50 percentiles, further referred as 50+ or 50-, of the CRF scores (using the ST test) and visualized the data through standard bar charts (Fig. 5).

Fig. 4 shows that bar charts based on standard assessment tools provide a very limited visualization of fitness data, preventing a clear interpretation of user's health status in comparison with normative data. Moreover, the different senior fitness tests have different

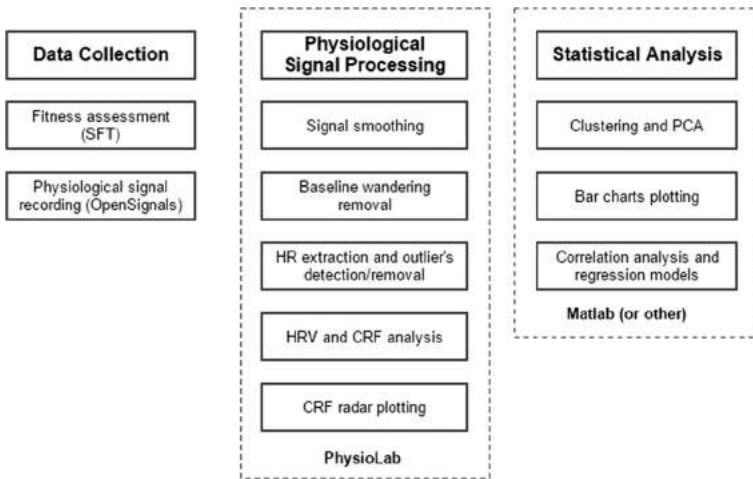


Fig. 4 Pilot study stages clustered by data collection, physiological signal processing and statistical analysis. PhysioLab was in charge of facilitating the analysis of the physiological signals before carrying out the statistical analysis

scales, which prevent a unified representation. Because some of the tests measure multiple domains and with the objective of improving data interpretation, we aggregated the subscores of each test according to the domains described in section 2.2.4: mental, ADL, balance, cardiorespiratory and musculoskeletal (Fig. 6).

Interestingly, despite the grouping strategy and data contextualization, a visual interpretation of the score data is not evident. The representation does not provide a holistic visual description of the users' health condition. These visualizations also do not include any normative data to be compared to. Thus, the question arises: Is PhysioLab capable to offer a context-aware visualization of the physiological data which can facilitate comparison of users under study with normative data?. In order to address the question we selected five of the seven physiological parameters extracted with PhysioLab after a PCA analysis (see section 2.2.4): $HR_{\text{difference}}$, HR_{max} , SDNN, EE and $VO_{2\text{max}}$. Based on the SFT data, we grouped the physiological responses according to the above described cardiorespiratory 50+ and 50- fitness profiles and represented them with the radar visualization option of PhysioLab. These cardiorespiratory radar plots provide an alternative graphical characterization of the CRF level of users, through physiological parameters (HR parameters in this case), using as reference normative data of older adults (pentagonal filled color areas) (Fig. 7).

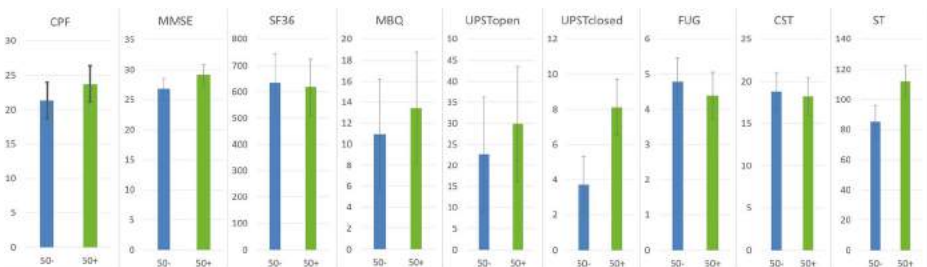


Fig. 5 Elderly fitness assessment tests divided by 50+ and 50- CRF profiles

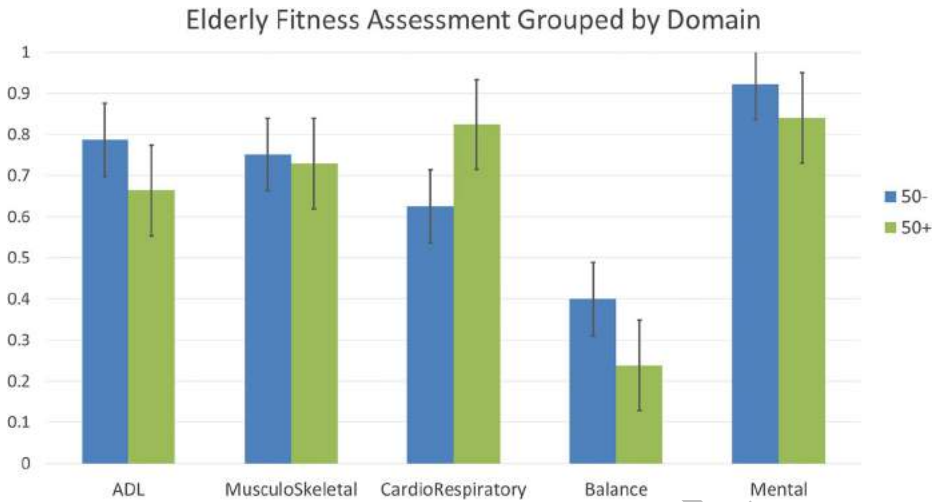


Fig. 6 Elderly fitness assessment grouped by domains and divided by poor and good CRF profiles

The cardiorespiratory radar plots evidence clear differences between groups, and the areas covered by each group are superimposed over age-matched normative data areas. This visualization offers more sensitivity and granularity to represent fitness related data, allowing a clear differentiation and interpretation of the CRF data. These differences can be seen in the VO_{2max} (50-: 31.9 ± 4.7 , 50+: 34.4 ± 2.9), $HR_{difference}$ (50-: 21.3 ± 6.9 , 50+: 24.6 ± 2.8), HR_{max} (50-: 160.6 ± 3.5 , 50+: 165.3 ± 3.8) and $SDNN$ (50-: 81.7 ± 57.9 , 50+: 86.7 ± 37.9) data. User data in the 50+ performance group are mostly located in the green zone of the cardiorespiratory radar plot, indicating an outstanding heart-activity regulation and aerobic capacity of these users during the exercise. Similarly, performance data of the 50- group are mostly in the yellow area, indicating medium levels of aerobic regulation.

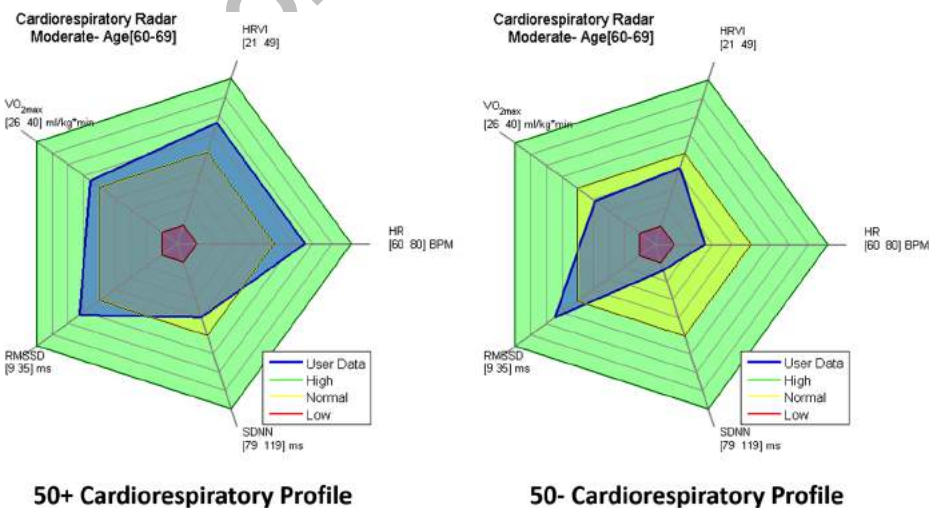


Fig. 7 CRF profiles represented by Radar Plots given by PhysioLab for 50+ (left) and 50- (right) performance groups

Interestingly, the Energy Expenditure (EE) parameter is consistent in both groups (50-: 6.2 ± 1.6 , 50+: 6.4 ± 1.3), indicating that both 50- and 50+ user groups performed the exercise with a similar intensity. Thus, the observed differences in physiological responses cannot be attributed to differences in training intensity. The use of PhysioLab's analysis and radar plotting can be of help in the evaluation and interpretation of physiological data in the CRF domain. However, we should explore whether the collected physiological data contain or not further information that allows us to explain other domains besides CRF.

3.2 ECG correlates of fitness performance

To unveil interactions between fitness tests/domains and the available HR parameters extracted from ECG data, a correlation analysis was performed. We first used the SFTs which reflect user's performance in specific fitness domains. Then, we used the domains from tests such as the MMSE and the SF36 to carry out a more detailed correlation analysis. The analysis revealed associations between each SFT assessment and multiple cardiac markers (Table 4). Significant correlations between HR parameters and fitness tests were found for HR_{difference} with CST ($r = -0.59$, $p < 0.05$) and SF36-mental health ($r = -0.53$, $p < 0.05$), HR_{resting} with MMSE- attention and calculation ($r = -0.51$, $p < 0.05$), HR_{max} with ST ($r = 0.51$, $p < 0.05$) and UPST_{open} ($r = 0.60$, $p < 0.05$), as well as SDNN ($r = 0.51$, $p < 0.05$) and RMSSD ($r = 0.49$, $p < 0.05$) with MMSE-language and praxis.

Only VO_{2max} and EE were not directly correlated with any fitness assessment. Subsequently, we used the SFT grouping approach by fitness domain. Once again, we explored the existing correlations of HR parameters in this case with fitness domains as opposed to tests in order to identify correlates that are more general. The correlation analysis showed significant correlations between HR_{difference} and musculoskeletal domain ($r = -0.59$, $p < 0.05$) and HR_{max} with cardiorespiratory ($r = 0.51$, $p < 0.05$) and balance ($r = 0.60$, $p < 0.05$) domains (Table 5).

The above two correlation analyses allowed us to identify the existence of test specific and domain specific correlates of the functional fitness. This suggests that the extracted HR parameters can be further exploited to infer fitness beyond CRF. However, despite the availability of this information, correlations only capture one-to-one linear relationships, leaving out interactions and other possible terms such as quadratic or cubic. Consequently, it remains unclear to what extent the above subset of HR parameters can be used to explain performance scores in fitness domains other than CRF.

Table 4 Correlation matrix of HR parameters and fitness tests/domains. Only significant correlations are displayed ($p < 0.05$)

Physiological features/Fitness tests	HR _{difference}	HR _{resting}	HR _{max}	VO _{2max}	SDNN	RMSSD	EE
CST	-0.5919	-	-	-	-	-	-
SF36-Mental Health	-0.5289	-	-	-	-	-	-
MMSE-Attention and calculation	-	-0.5067	-	-	-	-	-
ST	-	-	0.5142	-	-	-	-
UPST_EyesOpen	-	-	0.6065	-	-	-	-
MMSE-Language and Praxis	-	-	-	-	0.5077	0.4955	-

Table 5 Correlation matrix for HR parameters and fitness domains. Only significant correlations are displayed ($p < 0.05$)

Physiological features/ Fitness domains	HR _{difference}	HR _{resting}	HR _{max}	VO _{2max}	SDNN	RMSSD	EE
MusculoSkeletal	-0.5919	-	-	-	-	-	-
CardioRespiratory	-	-	0.5142	-	-	-	-
Balance	-	-	0.6038	-	-	-	-

3.3 Fitness prediction from HR parameters

Considering that physiological responses and assessment tests are continuous variables, and that interaction among HR features may exist, we decided to use a stepwise multiple linear regression modelling approach. Through this modelling approach we intend to establish linear regression equations with HR parameters as predictors and fitness domains as responses.

In the generation of the models, multiple combinations between variables and quadratic terms were considered. Table 6 describes the coefficients and intercepts for each model. Musculoskeletal ($p = 0.042$), cardiorespiratory ($p = 0.037$), balance ($p = 0.014$) and Mental ($p = 0.029$) domains showed statistically significant models, but not for ADL. HR_{difference} was present in three of the four models, showing a high influence of this parameter in multiple fitness domains.

R² model data shows that balance ($R^2 = 0.63$) and mental ($R^2 = 0.73$) models explain more than 50% of the data variation, while musculoskeletal ($R^2 = 0.46$) and cardiorespiratory ($R^2 = 0.37$) models were under 50%.

4 Discussion and conclusions

In this paper, we introduced PhysioLab: a multivariate signal toolbox created to simplify physiological signal processing, especially for out-of-the-lab fitness experiments. The toolbox is intended to assist both researchers and non-experts in the arduous task of processing physiological signals, allowing cross-comparisons between each signal, an automatic feature extraction with manual adjustments and providing a novel visualization. The software provides a wide variety of signal processing methods and artifact removal filters for EMG, ECG and EDA signals and it is

Table 6 Coefficients for each HR parameter for the multilinear regression models of musculoskeletal, cardiorespiratory, balance and mental domains

Predictors	Responses			
	Musculo Skeletal	Cardio respiratory	Balance	Mental
HR _{difference}	0.0627		0.1112	0.0289
HR _{resting}				0.0079
HR _{max}		0.0046	0.0088	
VO _{2max}				
SDNN			0.0014	
RMSSD				
HR _{difference} *HR _{rest}				-0.0004
HR _{difference} *HR _{max}	-0.0002			
HR _{resting} *VO _{2max}		0.0004		-0.0003
HR _{difference} ²	-0.0009		0.0025	
HR _{max} ²				
Intercept	0.7010	-1.0030	0.1348	0.3081

fully operated using a graphical user interface. Final parameters and processed signals can be exported easily by PhysioLab, which supports data from multiple low-cost physiological sensors. Multiple features from each signal are extracted to provide the most widely used and documented parameters for EMG (time and frequency domains), ECG (HR, HRV time domain and CRF parameters) and EDA (phasic and tonic) [15]. Additionally, PhysioLab contains a novel tool to visualize multiple physiological parameters in specialized fitness domains using radar plots, providing contextual normative data aiming at facilitate data interpretation. Specifically, we believe that the inclusion of the radar plots in the CRF domain allows: a) an easy comparison between individuals with average-profiles of the population, b) multiple comparisons between subject's exercise performances at different moments, c) versatility to include multiple HR-based metrics with normative data to assess users' performance. We believe these are powerful methods to assess the impact of a certain exercise program on the user's wellbeing.

Quantitative and qualitative analysis can be carried out through inspecting each PhysioLab's panel (analysis, visualization and features). Compared with other software tools [44], PhysioLab is a complete solution for physiological signal analysis, integrating three of the most widely used and non-invasive physiological signals, and guiding non-expert users in signal processing. The toolbox graphically shows the effects of multiple signal processing methods, which facilitates understanding and prevents common mistakes such as inclusion of motion artifacts.

The lack of specific contextual information and normative data often limits the interpretation of fitness data. As a case study, we demonstrated the use of PhysioLab for CRF assessment in a realistic environment. We processed ECG signals from 17 older adults recorded during a moderate physical activity task. Firstly, our concept of cardiorespiratory radar plots was used to present fitness profiles, in comparison to classic bar chart representations, which generally hide important information that describes the health status of the user. The cardiorespiratory radar plot approach revealed clear differences between CRF profiles by using five key HR parameters ($HR_{\text{difference}}$, HR_{max} , SDNN, EE and $VO_{2\text{max}}$) and normative data for the elderly population. The granularity of our representation to characterize cardiorespiratory profiles allows a more precise and intuitive assessment of aerobic endurance using field data. Further, the concept of cardiorespiratory radar plots can also be used to represent multiple performance data of the same user throughout various exercise sessions.

Secondly, in order to elucidate whether ECG data can be used to effectively describe not only CRF, but also a more holistic health status of users, a correlation analysis was performed. Initially, we used the standardized senior fitness tests to explore their correlations with the HR parameters. This analysis revealed that $HR_{\text{difference}}$ (the difference between HR during resting and exercise) had a negative correlation with users' functional independence evaluated through the CST. This finding is consistent with research indicating that a good balance between HR during resting periods and HR responses to exercise is essential to sustain good physical fitness performances [31]. Further, HR_{max} had a significant impact with multiple fitness tests. As expected, the ST was positively correlated with HR_{max} , confirming the importance of this variable in aerobic endurance [22]. SDNN and RMSSD parameters were correlated with the language and praxis score from the MMSE. Similarly to our study, past investigations showed that lower HRV measurements in older adults were associated with worse executive functions (assessed through the MMSE) [32].

When looking at correlates by fitness domain, cardiorespiratory and balance domains showed a positive correlation with HR_{max} . Additionally, musculoskeletal fitness correlates negatively with $HR_{\text{difference}}$, indicating an interaction between sympathetic activations (which mainly accelerate HR). Our findings are aligned with past investigations which emphasize a strong association between HRV and cognitive functions [43]. Normally, HR_{max} (or a fixed percentage) is used as a criteria for prescribing exercise activities in both rehabilitation and well-being programs [48].

Lastly, we generated four linear regressions models to explain the fitness domains in terms of the extracted physiological parameters. Interestingly, for balance and mental models, we discovered that just HR descriptors alone could explain more than the 50% of the data variation. The potential association of HRV with cognitive functions may be exploited associating underlying cognitive declines with poor cardiovascular prognosis as a noninvasive method for risk detection [1]. To our knowledge, this is the first systematic effort towards mining multiple HR parameters from ECG signals for predictive patterns, beyond what is represented in individual fitness domains. Finally, a future model driven exploration to describe fitness domains including other physiological data such as EMG or EDA can help us provide better physiological computing approaches to improve physical activity practice, exercise prescription and training personalization.

Limitations The present paper encloses both the presentation of a physiological computing toolbox for post-processing analysis and the execution of a feasibility study for its use in CRF assessment in a homogeneous elderly group. The study aimed to expose advantages in using physiological computing tools to involve HR and HRV analysis for fitness assessment as well as disentangle important statistical relations between fitness parameters and cardiac physiological measurements. Although a large number of correlation tests were performed, given our small sample size and the increase of type II errors, corrections for multiple tests were not performed to avoid hindering data interpretation. We considered each correlation on its own for the information it conveys, since all the predictors are linear and non-linear variables from HR, it is reasonable that we found multiple correlations of these variables with the fitness tests and domains. Besides, results from the regression models are consistent for each fitness domain and the correlations analysis confirmed the inherent relation between the cardiac regulation and the fitness tests [2]. More studies have to be addressed to fully understand the role of HR and HRV analysis complementing fitness assessment in the elderly population. Likewise, usability issues regarding the navigation and data visualization and interpretation by health professionals should be carefully studied to improve the likelihood of an extended use of the tool.

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