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Data Article

Cardiorespiratory DB: Collection of cardiorespiratory data acquired during normal breathing, deep breathing and breath holding

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A R T I C L E I N F O

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A B S T R A C T

The database is constituted by 50 datasets containing cardiorespiratory signals acquired from 50 healthy volunteer subjects (one dataset for each subject; 23 males and 27 females; age: 23±5 years) while performing normal breathing, deep breathing, and breath holding, and two spreadsheet files, namely the “SubjectsInfo.xlsx” and “DBInfo.xlsx” containing the metadata of subjects (including demographic data) and of acquired signals, respectively.
Cardiorespiratory signals consisted in simultaneously recorded 12-lead electrocardiograms acquired by the clinical M12 Global Instrumentation® digital Holter ECG recorder, and single-lead electrocardiograms and respiration signals acquired by the wearable chest strap BioHarness 3.0 by Zephyr.
The database may be useful to: (1) validate the use of wearable sensors in the acquisition of cardiorespiratory data during different respiration kinds, including apnea; (2) investigate the physiological association between cardiovascular and respiratory systems; (3) validate algorithms able to indirectly extract the respiration signal from the electrocardiogram; (4) study the fatigue level induced by a series of

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controlled respiration patterns; and (5) investigate the effect of COVID-19 infection on the cardiorespiratory system.

Specifications Table

Subject	Biomedical Engineering
Specific subject area	Cardiorespiratory data
Type of data	MATLAB binary files EXCEL files
Data collection	The database is constituted by 50 datasets (one for each subject) containing cardiorespiratory signals and by two spreadsheet files containing the metadata of subjects and of acquired signals, respectively. The clinical M12 Global Instrumentation® digital Holter ECG recorder (M12 GI Holter ECG; www.globalinstrumentation.com) and the wearable chest strap BioHarness 3.0 by Zephyr (BioHarness 3.0; www.zephyranywhere.com) were used to simultaneously acquire electrocardiograms ad respiratory signals in subjects performing normal breathing, deep breathing and breath holding.
Data source location	Acquisitions were performed at the Cardiovascular Bioengineering Lab, Department of Information Engineering, Università Politecnica delle Marche, Ancona, Italy, from November 28th, 2019 till May 18th, 2022.
Data accessibility	Repository name: Mendeley Data Data identification number: 10.17632/y7vs4yby9y.2 Direct URL to data: https://data.mendeley.com/datasets/y7vs4yby9y/2
Related research article	A. Sbrollini, M. Morettini, E. Gambi, L. Burattini, Identification of Respiration Types Through Respiratory Signal Derived From Clinical and Wearable Electrocardiograms, IEEE OJEMB 4 (2023) 268–274. doi: 10.1109/OJEMB.2023.3343557.

1. Value of the Data

The database may be useful to:

- validate the use of wearable sensors in the acquisition of cardiorespiratory data during different respiration kinds, including apnea, here simulated as breath holding;
- investigate the physiological association between cardiovascular and respiratory systems;
- validate algorithms able to indirectly extract the respiration from the electrocardiogram;
- study the fatigue level induced by a series of controlled respiration patterns;
- investigate the effect of COVID-19 infection on the cardiovascular system.

2. Background

Cardiorespiratory evaluation is essential in many healthcare applications. Indeed, it provides relevant information related to physiological mechanisms [1,2] and to pathological conditions [3,4]. Cardiac and respiratory signals are usually independently acquired by electrocardiography and spirometry, respectively [5,6]. Differently from electrocardiography, spirometry is uncomfortable for the subject. Thus, alternative indirect methodologies for evaluating respiration have been proposed. Electrocardiogram-derived respiration (EDR) consists in the extraction of the respiratory signal from the electrocardiogram (ECG) [7–10]. In the literature, EDR validation has been mainly performed by using ECGs acquired through standard clinical instrumentation during normal breathing. Standard 12-lead electrocardiography is more comfortable than spirometry. However, possibility of extracting EDR from ECGs acquired through wearable sensors is even more desirable since they are comfortable for the subjects and applicable in several different conditions (such as during sleep for apnea detection). Thus, the objective of this work was to acquired ECGs through standard clinical instrumentation and wearable sensors during different types of respiration, that are normal breathing, deep breathing and breath holding (to simulate apnea). The aim is to provide a new database for the evaluation of algorithms for EDR extraction and cardiorespiratory system evaluation.

3. Data Description

The database is constituted by 50 datasets containing cardiorespiratory signals (electrocardiograms and respiratory signals) acquired from 50 heathy subjects (one dataset for each subject) while performing different kinds of breathings, and two spreadsheet files, namely the "SubjectsInfo.xlsx" and "DBInfo.xlsx" containing the metadata of subjects (including demographic data) and of acquired signals, respectively.

Each dataset, referred as "S_ID" (where ID is the identifying number associated to the subject; with ID=1,2…50), contains two folders, namely "Clinical" and "Wearable". The "Clinical" folder contains the raw 12-lead electrocardiographic recording acquired by clinical instrumentation and stored as a MATLAB file called "ECG12.mat", a matrix composed of N rows (with N being different from subject to subject, and representing the total number of samples in each ECG lead) and 12 columns (representing leads I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6, respectively). Instead, the "Wearable" folder contains the raw single-lead electrocardiographic recording and the respiratory tracing acquired by wearable instrumentation and stored as MATLAB files called "ECG1.mat" and "RESP.mat", respectively, two vectors each composed of M rows (with M being variable and representing consecutive samples).

"SubjectsInfo.xlsx" contains: subject identifying number after anonymization and randomization (ID), sex (SEX, with 'M' being male and being 'F': female), age (AGE, in years), height (HEIGHT, in cm), weight (WEIGHT, in kg), smoking habit (SMOKER, with 'YES' for smokers, 'NO' for non-smokers, and 'EX' for ex-smokers), sport history ('YES': athlete; 'NO': non-athlete; 'EX': ex-athlete), and COVID-19 history (COVID19, with 'YES' if previously infected and 'NO' if never infected), and acquisition date (DATE, in gg/mm/yyyy format).

"DBInfo.xlsx" contains subject ID, deep-breath onset and end time (DBon_i and DBend_i, with $i = 1,2\ldots5$; s), and breath hold onset and end time (BHon_i and BHend_i, with $i = 1,2\ldots5$; s).

Overall, the database has a weight of 1.04 GB and can be downloaded from Mendeley Data (https://data.mendeley.com/datasets/y7vs4yby9y/2).

4. Experimental Design, Materials and Methods

The 50 subjects enrolled in the data acquisition were young healthy volunteers with no known history of cardiac, respiratory, or cardiorespiratory disease at the acquisition date. All of them gave their informed consent and provided demographic info immediately before signal acquisitions, which were undertaken in compliance with the ethical principles of Helsinki Declaration and approved by the institutional expert committee (Prot.n. 0029691).

The signal acquisitions were performed by means of clinical instrumentation, specifically the clinical M12 Global Instrumentation® digital Holter ECG recorder (M12 GI Holter ECG; www.globalinstrumentation.com) and of wearable instrumentation, specifically the wearable chest strap BioHarness 3.0 by Zephyr (BioHarness 3.0; www.zephyranywhere.com). The M12 GI Holter ECG was used to acquire the standard 12-lead electrocardiographic recordings [11,12] according to the Mason-Likar electrodes configuration (leads I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5, V6, respectively; sampling frequency of 1000 Hz). The M12 GI Holter ECG was resampled at 250 Hz. Instead, the BioHarness 3.0 was used to acquire the single-lead electrocardiographic recordings and the respiratory tracing (sampling frequency of 250 Hz for both of them) [12–15];

subjects were instructed to wear the chest strap so that the sensor was under the left arm, being this the optimal sensor location according to the device guidelines.

According to the acquisition protocol, the subject, after having worn the M12 GI Holter ECG and the BioHarness 3.0 and started recordings, had to perform two experimental tasks in random order: 1) alternate, for 5 times, at least 1 min of normal breathing and one deep breath; and 2) alternate, for 5 times, at least 1 min of normal breathing and maximum 30 s of continuous breath holding.

Recordings acquired by M12 GI Holter ECG and by the BioHarness 3.0 were synchronized by correlation analysis. Time instants (i.e., time delays with respect to beginning of recordings) in correspondence of which the five deep breaths and the five breath holds occurred were annotated.

Limitations

The main limitations of Cardiorespiratory DB are the following. Firstly, the database includes data from 50 young volunteers: thus, the number of subjects is limited, and the range of age is not represented in the database. Moreover, only the wearable sensor BioHarness 3.0 by Zephyr was used for data acquisition; data from other wearable sensors would be desirable, especially if testing algorithms based on artificial intelligence. Finally, the acquisition protocol required collection of demographic and cardiorespiratory data only; however, inclusion of other types of metadata (e.g., environmental temperature, subject activity etc.) would allow evaluation of techniques based on data fusion.

Ethics Statement

Participants gave their written informed consent and provided demographic info immediately before signal acquisitions, which were undertaken in compliance with the ethical principles of Helsinki Declaration and approved by the institutional expert committee (Prot.n. 0029691).

Data Availability

Cardiorespiratory DB (Original data) (Mendeley Data)

CRediT Author Statement

Agnese Sbrollini: Conceptualization, Methodology, Writing – original draft, Resources; **Ilaria Marcantoni:** Conceptualization, Investigation, Software, Resources, Writing – review & editing; **Tamara Lunghi:** Data curation, Resources; **Micaela Morettini:** Methodology, Visualization, Funding acquisition, Writing – review & editing; **Laura Burattini:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary Materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.dib.2024.110406.

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