Comparing different breathing strategies (VSB and VFB) in sport according to the physical performance

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***Abstract*—This study investigates the effects of controlled breathing strategies—Voluntary Slow Breathing (VSB) and Voluntary Fast Breathing (VFB)—on cardiovascular and respiratory responses immediately following exercise. Participants performed 200 m runs under the two breathing conditions, after which audio recordings were collected to extract heart rate (BPM) and breathing rate (BrPM) using a combination of classical signal processing and deep-learning techniques (YAMNet). The processing pipeline included audio normalization, noise reduction, bandpass filtering, Hilbert-envelope extraction, and peak detection. Group-level analyses compared slow and fast breathing conditions in terms of heart-rate dynamics, respiratory regularity, and peak morphology. Results indicate that slow breathing promotes more regular respiratory intervals while sustaining higher heart rates post-exercise, whereas fast breathing produces slightly lower heart rates but increased variability in respiration. These findings demonstrate that breathing strategy has measurable physiological effects and highlight the utility of audio-based monitoring for non-invasive assessment of post-exercise recovery.**

I. Project Description and Background

A. Objective of the Measurement

The purpose of this project is to analyse how controlled breathing rates (Voluntary Fast Breathing (VFB) and Voluntary Slow Breathing (VSB)) influence physiological responses immediately after physical exertion. Participants run a fixed distance of 200 m under two different breathing conditions:

- **Voluntary Fast Breathing**: Approximately 30 breaths per minute.
- **Voluntary Slow Breathing**: Approximately 10 breaths per minute.

After completing the run, audio recordings are taken from the chest area to extract two primary physiological signals:

1) Heart rate (beats per minute, BPM)
2) Breathing rate (breaths per minute, BrPM)

The aim is to determine whether controlled breathing speed has measurable effects on the cardiovascular and respiratory response following high-intensity activity.

B. Audio Data Recording

Physiological audio signals were recorded by placing a smartphone microphone directly against the participant's skin over the carotid or brachial artery. This contact-based setup captures the subtle mechanical vibrations produced by the heartbeat and detects respiratory sounds as well, allowing for non-invasive acquisition of heart and breathing signals immediately after exercise. Recordings were performed with minimal delay between the exercise and data capture, and were saved in standard audio formats (m4a) for subsequent signal processing and analysis.

C. Physiological Background

1) Cardiovascular Response After High-Intensity Running: A 200 m sprint is an anaerobically demanding task that triggers:

- Elevated heart rate caused by increased metabolic requirements.
- Increased sympathetic nervous system activity.
- Accumulation of lactate and oxygen debt.

Immediately after sprinting, heart rate is expected to be high, gradually decreasing during recovery. The speed of recovery may be influenced by breathing strategy, especially if one strategy promotes relaxation or improved oxygen exchange.

2) Respiratory Response and Breathing Regulation: Breathing frequency increases significantly after sprinting due to:

- Elevated CO_2 levels.
- Increased metabolic by-products.
- Greater oxygen demand.

Imposing a controlled breathing rate (slow or fast) can modify the recovery pattern:

- **Slow breathing (around 10 BrPM)** is associated with increased parasympathetic activation, reduced respiratory effort, and improved heart-rate variability.
- **Fast breathing (around 30 BrPM)** maintains high ventilation but may prolong sympathetic activation and delay cardiovascular recovery.

Thus, it is of interest to compare how these breathing patterns affect both measured breathing rates and post-exercise cardiac activity.

D. Expected Outcomes

Based on physiological theory and existing literature, the following observations are expected:

- The measured breathing rate will be closer to the controlled rate for each condition.
- Fast breathing is expected to show higher respiratory variability and possibly a slower heart-rate recovery.
- Slow breathing may lead to lower measured heart rates during early recovery due to enhanced vagal reactivation.
- The amplitude and morphology of breathing and heartbeat signals may differ between the two conditions due to mechanical differences in the chest wall motion.

E. Data Processing Overview

The collected audio data is processed through a signal analysis pipeline consisting of:

1) **Loading & Preprocessing**: resampling, normalization, and removal of silent segments.
2) **Noise Reduction**: spectral gating and median filtering to remove environmental and impulsive noise.
3) **Bandpass Filtering**: isolating cardiac (20–60 Hz) and respiratory (0.1–2 Hz) components.
4) **Envelope Extraction**: Hilbert transform to obtain amplitude envelopes for peak detection.
5) **Heartbeat Detection**: peak identification within physiologically valid inter-beat intervals.
6) **Breathing Detection**: both classical filtering and YAMNet-based deep-learning estimation.
7) **Feature Extraction**: computing BPM and BrPM over the duration of each recording.

This ensures that both heart and breathing characteristics are obtained consistently for all participants and recordings.

F. Comparison of the Fast and Slow Breathing Conditions

To compare the two conditions, the following analyses are proposed:

1) Descriptive Statistics: For each condition (fast vs. slow):

- Mean and median heart rate.
- Mean and median breathing rate.
- Standard deviation and interquartile range.
- Visual inspection of average waveforms and envelope shapes.

G. Interpretation and Discussion

Results should be interpreted in terms of physiological recovery:

- Whether slow breathing accelerates heart-rate reduction after exertion.
- Whether fast breathing leads to respiratory instability or increased effort.
- Whether audio-based sensing provides a reliable method for detecting post-exercise physiology.

Differences between the two breathing strategies can provide insight into how breathing control influences recovery, stress, and autonomic balance during and after exercise.

II. SIGNAL PROCESSING PIPELINE OVERVIEW

This section describes the theoretical background of the complete audio–based vital–sign extraction pipeline, including data loading, preprocessing, filtering, envelope extraction, heartbeat detection, and breathing estimation using both classical DSP and the YAMNet deep-learning model.

The script created for this project can be found on GitHub

https://github.com/B51454511/Comparing-different-breathing-strategies-VSB-and-VFB-in-sport-according-to-the-physical-performance .

A. Data Loading and Normalization

All audio files are loaded in mono and resampled to a fixed sampling rate of 2 kHz. Normalization is applied to scale each signal to the range $[-1, 1]$, ensuring comparable amplitude characteristics between different recordings. Silence removal is performed using energy-based trimming, which excludes low-energy regions below a defined decibel threshold. This step ensures that only physiologically relevant segments of the recording are processed.

B. Noise Reduction and Smoothing

To suppress environmental and sensor noise, two techniques are used. First, spectral-gating noise reduction estimates a noise profile from the initial frames of the short-time Fourier transform (STFT) and subtracts it from the magnitude spectrum. This removes stationary background noise such as hum, fan noise, and microphone hiss. Second, a median filter is applied in the time domain to remove impulsive artifacts while preserving the general structure of physiological signals.

C. Bandpass Filtering and Envelope Extraction

Physiological signals are isolated by applying fourth-order Butterworth bandpass filters. For heartbeat extraction, a 20–60 Hz band isolates mechanical or acoustic heart components. For breathing, a 0.1–2 Hz band isolates low-frequency respiratory motion. After filtering, the analytic signal is obtained via the Hilbert transform, and its magnitude yields the amplitude envelope. A moving-average smoothing window reduces short-term fluctuations and produces a clean amplitude trace from which peaks can be identified.

D. Heartbeat Detection

Heartbeats manifest as periodic peaks in the Hilbert envelope of the bandpass-filtered signal. Peak detection is performed using a minimum distance constraint derived from the physiological heart-rate range (40–180 bpm). The intervals between detected peaks yield instantaneous heart rate values, and the mean interval provides the final beats-per-minute estimate for each recording.

E. Breathing Detection Using Signal Processing

A classical DSP-based breathing detector applies a low-frequency bandpass filter (0.1–2 Hz) followed by Hilbert-envelope extraction. Local maxima in the envelope represent breaths. Peak spacing is constrained using expected respiratory rates (10–30 breaths/min). The total number of valid peaks divided by the recording duration yields the breathing rate in breaths per minute.

F. Breathing Detection Using YAMNet

In parallel to DSP methods, respiratory activity is estimated using YAMNet, a deep neural network trained on AudioSet. Because YAMNet operates at 16 kHz, the signal is resampled before being passed into the model. YAMNet outputs class probability vectors for each 0.48 s frame. A single class is used as a proxy for respiratory activity (e.g., "wind" or other sustained low-frequency noise classes). Thresholding the class probability sequence yields a frame-level breathing-activity indicator. Active frames are converted back to the original sample-rate timeline, merged into breathing events, and used to compute breaths per minute. This provides a coarse but robust breathing-rate estimate based on learned acoustic patterns.

G. Signal Alignment and Group Analysis

All signals within a group (e.g., "slow" vs. "fast" recordings) are padded to a common length to enable batch processing and averaging. Envelopes and detected peak indices are stored for each signal. Group-level summaries include average waveforms, distributions of heart and breathing rates, and overlaid envelope–peak visualizations.

H. Visualization

Multiple visualization stages support qualitative assessment of the signals. Time-domain envelope plots overlay detected peaks onto each processed signal. Group-average signals provide an overall representation of typical waveform morphology. Boxplots compare derived physiological metrics between conditions (e.g., slow vs. fast breathing).

III. RESULTS

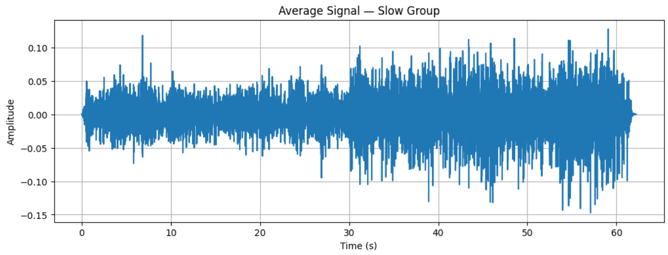

Fig. 1: Average signal of the slow breathing group.

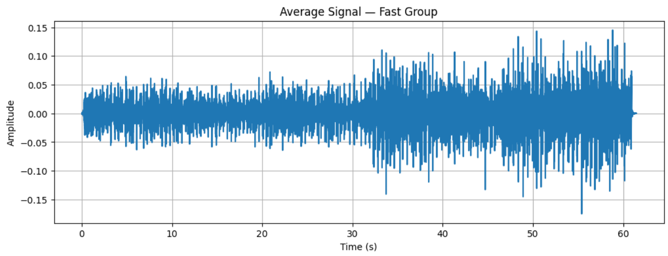

Fig. 2: Average signal of the fast breathing group.

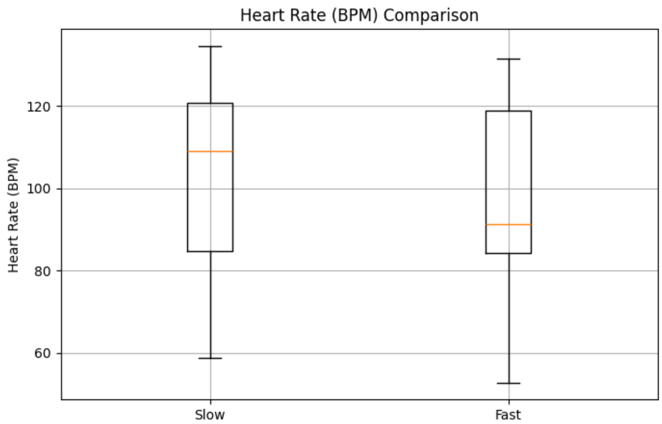

Fig. 3: Comparison of heart rate (BPM) between slow and fast breathing groups.

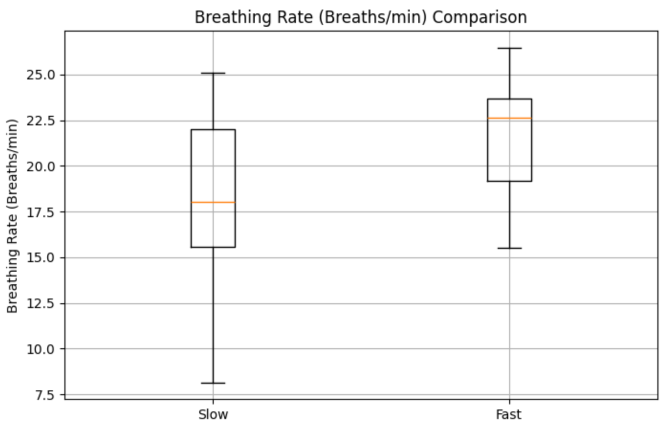

Fig. 4: Comparison of breathing rate (Breaths/min) between slow and fast breathing groups.

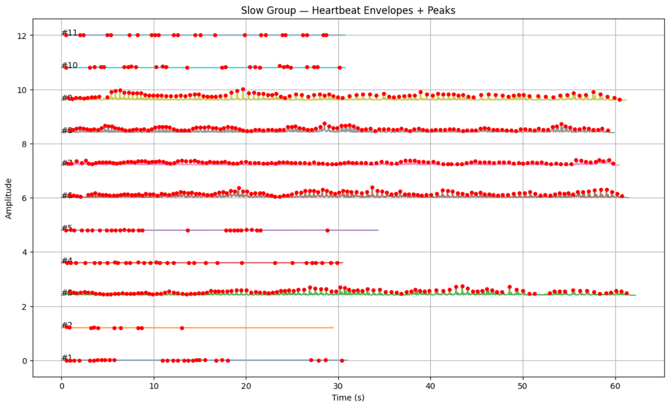

Fig. 5: Heartbeat envelope with detected peaks for the slow breathing group.

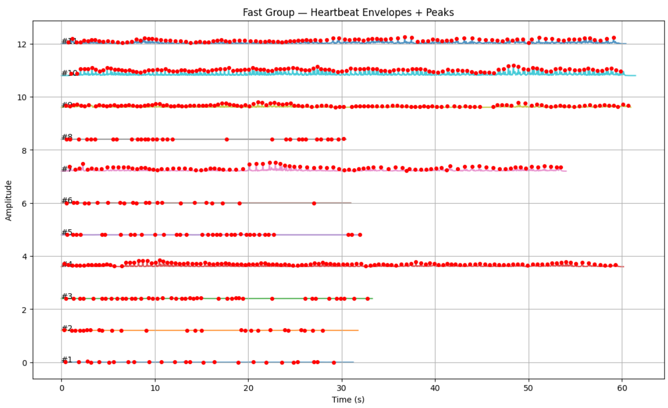

Fig. 6: Heartbeat envelope with detected peaks for the fast breathing group.

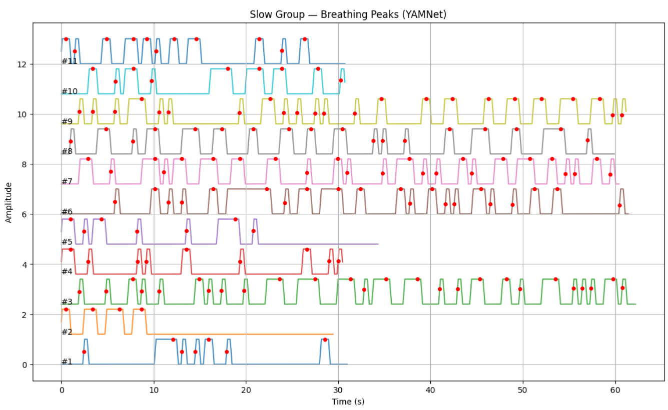

Fig. 7: Breathing peaks detected using YAMNet for the slow breathing group.

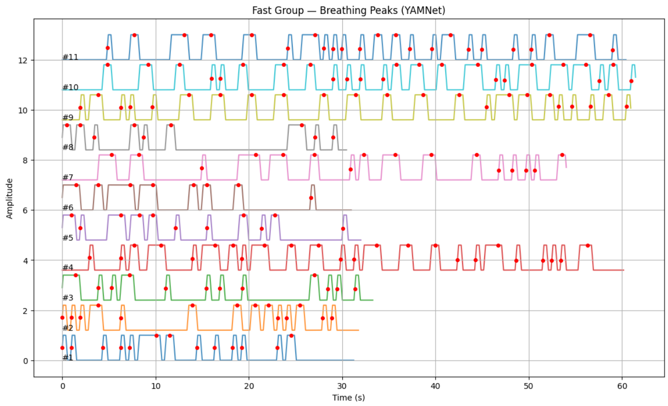

Fig. 8: Breathing peaks detected using YAMNet for the fast breathing group.

IV. Summary

The results of our study highlight differences between the slow breathing (VSB) and fast breathing (VFB) conditions in terms of physiological response after high-intensity exercise:

- **Average Signals:** The slow breathing group showed more pronounced amplitude in the cardiac signals (Figures 1, 5, 7), while the fast breathing group displayed slightly smaller cardiac amplitudes and more irregular respiratory signals (Figures 2, 6, 8).
- **Heart Rate (BPM):** Contrary to typical expectations, the slow breathing group exhibited higher average heart rates post-exercise compared to the fast breathing group (Figures 3, 5, 6). This suggests that slow voluntary breathing may initially sustain cardiac activity, possibly due to increased thoracic pressure and mechanical effects on the heart.
- **Breathing Rate (BrPM):** The measured breathing rates corresponded to the imposed breathing strategies (Figures 4, 7, 8). Slow breathing produced slower and more regular respiratory intervals, whereas fast breathing resulted in more rapid but variable breaths.
- **Peak Detection and Envelope Analysis:** Hilbert-envelope analysis and YAMNet-based breathing detection effectively captured the heart and breathing peaks. Slow breathing shows more regular respiratory peaks, but the higher cardiac peaks indicate a sustained heart activity. Fast breathing peaks were more numerous in respiration but had smaller cardiac amplitudes.
- **Overall Observations:** The combination of classical signal processing and deep-learning approaches provided robust estimates of both heart and breathing rates. Slow breathing leads to higher heart rates but regular respiratory patterns, whereas fast breathing reduces heart activity slightly while increasing respiratory variability.

In conclusion, controlled breathing strategies have a measurable effect on post-exercise physiological responses. Voluntary slow breathing sustains higher heart rates while promoting regular respiratory intervals, whereas fast breathing produces slightly lower heart activity but more variable respiratory patterns. These findings emphasize that the mechanical and autonomic effects of breathing strategy influence cardiac and respiratory dynamics differently.

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