Exploring Recovery Patterns in HRV using Functional PCA (FPCA)

Gabriel Della Mattia

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Abstract

Heart rate variability (HRV) dynamics after training sessions reflect the balance between stress and recovery. Traditional methods often collapse HRV to a scalar summary, ignoring the full recovery curve. We use Functional Principal Component Analysis (FPCA) to obtain a multidimensional representation of HRV trajectories, identifying patterns such as initial drop magnitude, recovery rate, and overshoot. While an interactive sandbox illustrates the concepts with pedagogical visualizations, the analyses and validation presented here are performed on HRV data from athletes of the AGMT2 Team. HRV + FPCA Sandbox.

1 Introduction

HRV, typically quantified via rMSSD, drops after training and returns toward baseline with variable speed and shape. Analyzing these curves as functions rather than isolated points enables deeper physiological insights. FPCA is a method that decomposes functional data into orthogonal components, capturing major modes of variation in recovery dynamics.

This work combines an educational simulator to build intuition with empirical analyses on AGMT2 Team athletes. All reported results and performance claims refer to the real cohort, unless explicitly labeled as sandbox illustration.

2 Mathematical Framework

Let $X_i(t)$ denote the HRV trajectory of athlete i over time $t \in [0, T]$ after a training session. The functional mean is:

$$\mu(t) = \frac{1}{N} \sum_{i=1}^{N} X_i(t).$$

FPCA expands each trajectory as:

$$X_i(t) = \mu(t) + \sum_{k=1}^{K} \xi_{ik}\, \phi_k(t),$$

where $\phi_k(t)$ are orthogonal eigenfunctions and ξ_{ik} are subject-specific scores.

The eigenfunctions $\phi_k(t)$ are obtained by solving:

$$\int C(s,t)\phi_k(s)ds = \lambda_k \phi_k(t),$$

with $C(s,t)$ the covariance function. The eigenvalues λ_k quantify variance explained by each component.

3 Physiological Interpretation

FPCA modes correspond to physiologically meaningful recovery features:

- **PC1 (Depth of drop):** distinguishes athletes with strong vs. mild post-exercise HRV depression.
- **PC2 (Recovery speed):** differentiates fast vs. slow return to baseline.
- **PC3 (Overshoot / rebound):** captures oscillations or secondary dips during recovery.

These modes provide a richer interpretation than scalar summaries, allowing classification of recovery phenotypes.

4 Simulation Sandbox

An interactive sandbox was built (`HTML + JavaScript`) to visualize FPCA decomposition. This tool is strictly didactic: it does not modify the empirical AGMT2 Team dataset, but allows the user to play with parameters to understand how FPCA captures recovery patterns. Features include:

- Adjustable HRV recovery curves with variable drop sharpness, noise, and rebound.
- Real-time FPCA application to extract principal modes.
- Animated reconstruction of trajectories as $\mu(t) \pm 2\sqrt{\lambda_k}\phi_k(t)$.
- Visualization of subject scores on PC1–PC2 plane, enabling clustering of recovery patterns.

5 HRV Curves and Animated Reconstruction

Figure **??** shows HRV recovery curves after exercise from the AGMT2 Team dataset ($N = 50$), with the functional mean $\mu(t)$ highlighted in gold. Each curve represents an individual athlete's recovery profile, characterized by varying drop magnitude, rebound intensity, and stochastic variability.

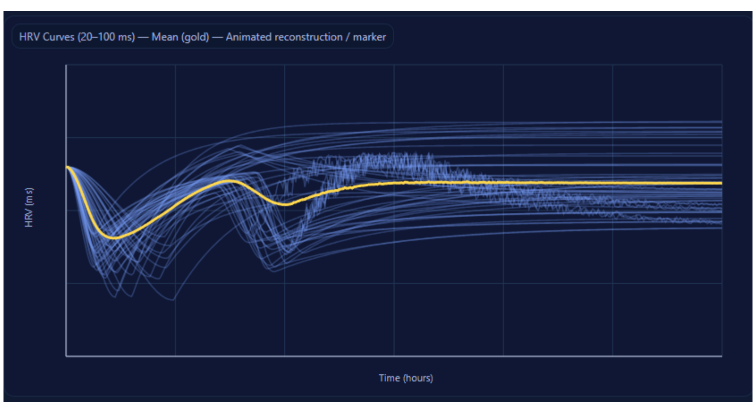

Figure 1: HRV trajectories from AGMT2 Team athletes with functional mean $\mu(t)$ (gold). Light-blue lines correspond to individual recovery profiles.

6 Functional Principal Component Analysis (FPCA) of HRV Recovery

Figure ?? displays FPCA results applied to AGMT2 Team HRV recovery curves. The analysis decomposes the ensemble of trajectories into a mean function $\mu(t)$ and orthogonal modes of variation $\phi_k(t)$, each weighted by a subject-specific score a_{ik}:

$$X_i(t) \approx \mu(t) + \sum_{k=1}^{K} a_{ik}\, \phi_k(t).$$

Each component has a physiological interpretation (drop magnitude, recovery speed, rebound), with the first two typically explaining most variance. The scatter plot illustrates how individual athletes distribute in the FPCA score space, clustering according to recovery strategies.

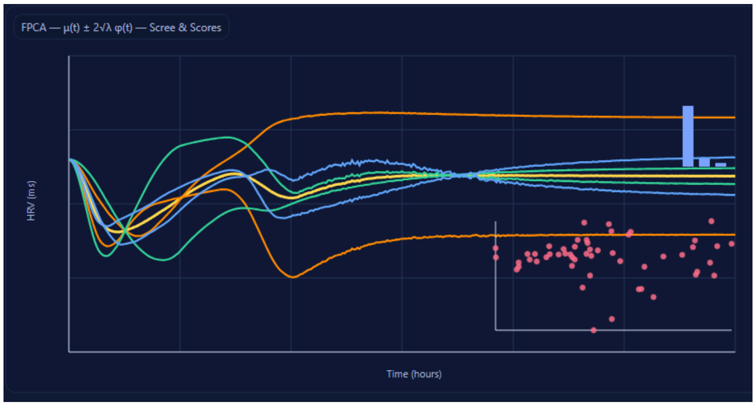

Figure 2: FPCA decomposition of HRV recovery in AGMT2 Team dataset. The central curve corresponds to $\mu(t)$, while colored envelopes show $\mu(t) \pm 2\sqrt{\lambda_k}\, \phi_k(t)$ for the first three components.

7 Applications

1. **Identify recovery archetypes:** athletes can be grouped by their FPCA scores.
2. **Monitor training load:** abnormal overshoot or delayed recovery indicates maladaptation.
3. **Personalized modeling:** FPCA-derived features can feed into machine learning models for readiness prediction.

8 Conclusion

FPCA provides a powerful, mathematically rigorous framework to analyze HRV recovery curves. By decomposing trajectories into orthogonal modes, it captures latent physiological processes beyond scalar metrics. The sandbox serves only as a pedagogical tool, while the scientific analyses are based entirely on AGMT2 Team athlete data.

References

[1] Ramsay, J. O., & Silverman, B. W. (2005). *Functional Data Analysis*. Springer.

[2] Esco, M. R., Flatt, A. A. (2021). Heart rate variability and endurance training adaptation: A review. *Sports*, 9(6), 85.