Offline Change-Point Detection for 3D Motion Capture Data

Postdoctoral position (1 year)

Centre Borelli, ENS Paris-Saclay

Keywords

change-point detection, geometric signal processing, statistics, 3D motion capture

Presentation of the lab

This postdoc will take place at the Centre Borelli (ENS Paris Saclay). The Centre Borelli is a multidisciplinary research unit focusing on all applications of mathematics, neuroscience and biomedical research. It brings together multidisciplinary teams of mathematicians and experts in medicine, physics, mechanics, biology and engineering to conduct research driven by real data and use cases from science and industry.

Environment

The postdoctoral researcher will have the opportunity to fully integrate into an interdisciplinary team of mathematicians, computer scientists, biologists and clinicians. If successful, the postdoc may lead not only to scientific publications, but also to a valorization project. The postdoctoral researcher will also attend weekly laboratory seminars.

Contract and required skills

The position is available for a 12-month (1-year) term beginning in the fall of 2026. The salary will be determined based on the candidate's professional experience.

The candidate should hold a PhD in signal processing, statistics, machine learning, or applied mathematics, with expertise in Riemannian geometry and/or change-point detection. Proficiency in Python and strong programming skills. Experience in video processing, 3D signal analysis would be a plus as well as interest in biomedical applications.

How to apply

Applicants must submit an application package consisting of a resume and a list of publications to laurent.oudre@ens-paris-saclay.fr

Context

The Centre Borelli is involved in analyzing various protocols designed to quantify human behavior. Examples include projects that use cameras to study human and animal behavior, as well as projects that use 3D markers (motion capture) to study movement. The 3D motion capture systems (Vicon, Qualisys) and vision-based pose estimation pipelines (MediaPipe, DeepLabCut) used in these projects produce, at each time step t, the 3D positions of k anatomical landmarks: $\mathbf{X}_t \in \mathbb{R}^{3\times k}$. These data have a rich geometric structure: the shape of the skeleton lives in Kendall's shape space Σ_k^3, while inter-landmark correlations live in the manifold of symmetric positive-definite matrices $\mathcal{S}_{++}(d)$.

Since the generated signals are non-stationary, one approach to processing them is to use offline change-detection algorithms, which allow the signals to be divided into homogeneous time segments. This typically involves solving a discrete optimization problem of the type [1][2]

$$\hat{\mathcal{T}} = \arg\min_{\mathcal{T}} \left[\sum_{(a,b)\in \text{seg}(\mathcal{T})} c(y_{a:b}) + \beta |\mathcal{T}| \right], \tag{1}$$

where $c(y_{a:b})$ measures the homogeneity of the signal on segment $[a, b]$, $\mathcal{T}$ is a set of change points, and $\beta > 0$ is a penalty.

The central question of this proposal: how to define cost functions c adapted to the geometric structure of skeleton data, and what mathematical properties must they satisfy so that standard change-point algorithms apply with their usual guarantees?

Research proposal

The suggested research topics are intentionally presented as open-ended questions so that candidates can adapt them to their own interests and choose the topic that best aligns with their previous work.

- **Cost Functions on $\mathcal{S}_{++}(d)$ for Inter-Landmark Covariances**. One approach to processing this 3D data is to work with the covariance matrix, which encodes the structural relationships between the sensors. Several cost functions can be used to detect changes in structures encoded using covariance matrices; these include, the Log-Euclidean Metric (LEM) [6], the Riemannian Wishart cost with Affine-Invariant Metrix (AIM) [5] or the Riemannian kernel cost [3]. These cost functions raise several questions regarding the applicability of these measures to the CDP framework (scalability, the ability to compute the cost function efficiently and recursively, the possibility of implementing effective pruning strategies, etc.) or to calibration problems.
- **Cost Functions for Skeleton Graph Signals.** One approach involves encoding the skeleton structure as a graph. This perspective links the problem to the Graph Signal Processing framework [7]. Recent works have shown that graph prior knowledge can help to parametrize covariance matrices and improve the CPD task in noisy/scarse data setting [8]. Several lines of research could be investigated such as the introduction of anatomical sparsity constraints in the graph and joint estimation of change-points and graph structure.
- **Cost Functions on Kendall's Shape Space Σ_k^3.** One last idea would be to work directly on the shape domain thanks to geometrical distances (such as Procrutes [4]). One big challenge would be to define a cost in this domain (e.g. with a Fréchet variance cost) and to introduce relaxation techniques and/or proxy distances that would keep all computations tracktable.

References

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