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Statistical Modelling by Geodesics of Critical Gait Event Motion

Stephan F. Huckemann¹, Michael Pierrynowski², Tara Kajaks², Peter Kim³ and Ja-Yong Koo⁴

> ¹Univ. of Göttingen, ²McMaster Univ. Hamilton, ³Univ. of Guelph and ⁴Korea Univ.

Geometry for Anatomy Banff International Research Station Aug. 29 – Sep. 2, 2011



supported by

DFG Grant HU 1575/2-1



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Discribing the knee frame, Wu and Cavanagh (1995).

Geodesic Statistics of Gait Events

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Angular motion of one gait cycle, Chao et al. (1983).

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Why?

- early diagnosis of degenerative effects,
- early diagnosis of neuromuscular processes,
- planning and evaluation of therapeutic interventions.

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Why?

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How? Traditionally:

- Functional Data Analysis,
- curve registration,
- warping,
- how incorporate 3D information?



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Biomedical Gait Analysis

How? Traditionally:

- Functional Data Analysis,
- curve registration,
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- how incorporate 3D information?

Today:

- Approximation by geodesics in SO(3)
- registration by critical events
- → statistics in the space of geodesics.





Further Plan

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Geodesic Statistics of Gait Events

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- 1 Biomedical Gait Data
- 2 Statistics on Manifold: Test for Common Means
- Differential Geometry for the Space of Geodesics on SO(3)



Data Analysis: Evaluate an Intervention

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Asymptotics for Manifold Means

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Ingredients:

• \mathcal{C}^2 Manifold M, $\rho: M \times M \to [0,\infty)$ is \mathcal{C} .

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Asymptotics for Manifold Means

Ingredients:

- \mathcal{C}^2 Manifold M, $\rho: M \times M \to [0, \infty)$ is \mathcal{C} .
- $X : \Omega \to M$ is a random element, $X_1, \ldots, X_n \stackrel{i.i.d}{\sim} X$.

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- Generalized Fréchet *ρ*-means:

$$E(X) = \operatorname*{argmin}_{p \in M} \mathbb{E}(\rho(p, X)^2), \ E_n = \operatorname*{argmin}_{p \in M} \sum_{j=1}^n \rho(p, X_j)^2$$

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$$\phi: \boldsymbol{U} o \mathbb{R}^m$$
 local chart near $\mu \in \boldsymbol{E}(\boldsymbol{X}).$

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• $\phi: U \to \mathbb{R}^m$ local chart near $\mu \in E(X)$. **Theorems:** + technical conditions, e.g. *M* compact. SLLN: $E_n \to E(X)$ a.s. (Ziezold (1977)).

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• $\phi: U \to \mathbb{R}^m$ local chart near $\mu \in E(X)$.

Theorems: + technical conditions, e.g. *M* compact.

SLLN: $E_n \rightarrow E(X)$ a.s. (Ziezold (1977)).

CLT : if is μ unique, if ρ^2 is C^2 on supp(X) and if $\mu_n \in E_n$ is a measurable choice then there are matrices A_{ϕ}, Σ_{ϕ} such that

$$A_{\phi}\sqrt{n}(\phi(\mu_n)-\phi(\mu)) \stackrel{d}{\rightarrow} \mathcal{N}(\mathbf{0}, \Sigma_{\phi})$$

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(Huckemann (2011)).

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A Simple Geometry: *M* and ρ for $\Gamma(SO(3))$

• \exists a smooth manifold structure $SO(3) \cong S^3/S^0 = \mathbb{R}P^3$

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- The action $(x, v) \xrightarrow{g} (x, v)g$ of O(2) =: G is isometric on $M(4, 2) \cong \mathbb{R}^{4 \times 2}$,

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• it's free on $F := M(4,2) \setminus \left\{ (x, \alpha x) \in M(4,2) : \alpha \in \mathbb{R} \right\}$

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- with $N := \{Z \in F : Z^T Z = I_2\},\ \Gamma(SO(3)) \cong N/G =: M \subset F/G \text{ is a smooth submanifold}$

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- [x, v] is a cut point of [y, w] ∈ N/G in F/G, write
 [x, v] ∈ C([y, w]) ⇔ the two great circles intersect orthogonally.

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Two Sample Test for Common Ziezold Mean Geodesics

Single *j*-th (*j* = 1,..., *n*) gait cycle → compute geodesic approximation *γ_j* in or out of on of three critical events (begin stance, mid stance, end stance),

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• two i.i.d. samples $\gamma_1, \ldots, \gamma_{n_1}$, and $\gamma_{n_1+1}, \ldots, \gamma_{n_1+n_2} \in \Gamma(SO(3)), n_1 + n_2 = n.$

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- *H*₀: equal Fréchet *ρ*-means.
- $[\mu^{(k)}], k = 0$, is candidate for ρ -mean.

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- Algorithm $k \rightarrow k + 1$:
 - Bring lifts of $\gamma_1, \ldots, \gamma_n$ into optimal position to $\mu^{(k)}$ if $\forall \gamma_j \notin C([\mu^{(k)}])$; then unique, else error.

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 - Compute their extrinsic mean $\mu^{(k+1)}$ in $N \subset F$ (unique!).

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Stop if ρ([μ^(k+1)], [μ^(k)]) < ε.

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 - Compute their extrinsic mean µ^(k+1) in N ⊂ F (unique!).
 - Stop if $\rho([\mu^{(k+1)}], [\mu^{(k)}]) < \epsilon$.
- Project o.p. γ₁,..., γ_n orthogonally to T_{μ^(k)}N ⊂ M(4,2).

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 - Stop if $\rho([\mu^{(k+1)}], [\mu^{(k)}]) < \epsilon$.
- Project o.p. γ₁,..., γ_n orthogonally to T_{μ^(k)}N ⊂ M(4,2).
- Under H_0 and $n_1/n_2 \xrightarrow{n \to \infty} 1$ the corresponding Hotelling T^2 -statistic is asymptotically Hotelling T^2 -distributed.

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Evaluate an Intervention

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Michael Pierrynowski and Tara Kajaks:

• Collect 10 gait cycles of 8 healthy individuals,

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Evaluate an Intervention

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- Collect 10 gait cycles of 8 healthy individuals,
- expose them to half an hour of kneeling,

Huckemann, Pierrynowski, Kajaks, Kim, Koo

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- Geometry
- Data Analysis
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Evaluate an Intervention

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- Collect 10 gait cycles of 8 healthy individuals,
- expose them to half an hour of kneeling,
- take another 10 gait cycles of each of the 8 subjects.

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Evaluate an Intervention

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- Collect 10 gait cycles of 8 healthy individuals,
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- take another 10 gait cycles of each of the 8 subjects.
- Did the stretching change (e.g. loosen up) the gait pattern?

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Evaluate an Intervention

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Evaluation into beginning of stance. Black: before, red: after intervention.

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, :	subjects	1	2	3	4
.,	in: begin stance	1.08 <i>e</i> – 12	2.60 <i>e</i> – 06	0.446	5.43 <i>e</i> – 05
	out: begin stance	4.64 <i>e</i> – 08	3.63 <i>e</i> – 07	0.013	8.45 <i>e</i> – 05
	in: mid stance	1.54 <i>e</i> – 06	7.09 <i>e</i> – 05	2.52 <i>e</i> – 03	0.032
	out: mid stance	1.70 <i>e</i> – 08	1.14 <i>e</i> – 06	0.800	0.029
	in: end stance	3.35 <i>e</i> – 08	1.23 <i>e</i> – 07	4.62 <i>e</i> – 03	0.873
	out: end stance	1.29 <i>e</i> – 09	4.98 <i>e</i> - 07	0.010	0.226
s	subjects	5	6	7	8
	in: begin stance	0.190	0.058	6.29 <i>e</i> – 06	0.028
	out: begin stance	0.057	0.459	0.015	0.024
	in: mid stance	0.180	0.865	9.20 <i>e</i> – 03	4.69 <i>e</i> – 03
	out: mid stance	0.033	0.255	0.060	5.42 <i>e</i> – 04
	in: end stance	7.27 <i>e</i> – 03	0.016	7.05 <i>e</i> – 03	0.978
	out: end stance	1.39 <i>e</i> – 03	5.70 <i>e</i> – 04	6.87 <i>e</i> – 03	0.039

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Bonferoni correction yields:

All subjects feature (all but subject 3: highly) significant gait change after intervention.

(high significance level 0.01 \rightarrow 0.01/48 \approx 2e – 03)

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Add on: Discriminate Subjects

Into beginning of stance, before intervention:

subjects	2	3	4	
1	2.52 <i>e</i> – 06	4.78 <i>e</i> – 03	2.86 <i>e</i> - 10	
2		5.45 <i>e</i> – 05	1.65 <i>e</i> – 08	
3			2.46 <i>e</i> - 03	
subjects	5	6	7	8
1	4.27 <i>e</i> – 10	3.08 <i>e</i> – 08	4.76 <i>e</i> – 08	2.43 <i>e</i> – 05
2	4.89 <i>e</i> – 06	4.49 <i>e</i> – 04	4.00 <i>e</i> – 08	0.034
3	0.024	6.62 <i>e</i> – 04	1.22 <i>e</i> – 03	0.011
4	4.34 <i>e</i> – 04	2.08 <i>e</i> – 08	2.72 <i>e</i> – 13	5.12 <i>e</i> – 06
5		8.76 <i>e</i> – 06	1.26 <i>e</i> – 11	5.74 <i>e</i> – 05
6			2.13 <i>e</i> – 10	9.48 <i>e</i> – 03
7				1.37 <i>e</i> – 09

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6			2.13 <i>e</i> – 10	9.48 <i>e</i> – 03
7				1.37 <i>e</i> – 09

Bonferoni (0.01 \rightarrow 0.01/28 \approx 3.6e – 03) yields here that

All subjects discriminate highly significantly (except 8 from 2, 3, 6 and 3 from 5).

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 Geodesic approximation for in– and out–motion of critical gait events.

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- Geodesic approximation for in– and out–motion of critical gait events.
- Ziezold type statistics: sample space is a quotient M/G, M embedded in a Euclidean space \rightarrow the "quotient of the extrinsic mean".

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Conclusions

- Geodesic approximation for in– and out–motion of critical gait events.
- Ziezold type statistics: sample space is a quotient M/G, M embedded in a Euclidean space \rightarrow the "quotient of the extrinsic mean".
- Nice mixture of intrinsics and extrinisics → broad applicability (e.g. uniqueness) and computationally simple.

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Conclusions

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Conclusions

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Geodesic approximation for in– and out–motion of critical gait events.

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- Application to biomedical gait analysis:
- individual highly discriminatory gait signature at critical gait events (over all events, before and after intervention),
- significant change in gait pattern after intervention.
- N.B.: Loosening the knee? No! No significant change of variances after intervention. But: motor control alteration.

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Geodesic Statistics of Gait Events

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Grant for a PhD student at Univ. of Göttingen available starting in fall 2011 or later: statistics of geometry and differential equations in biomechanics

References

Statistics of Gait Events Huckemann, Pierrynowski, Kajaks, Kim,

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