Towards the Analysis of Movement Variability in Human-Humanoid Interaction

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Outline

I. Introduction – Movement Variablity

II. Methods – Reconstructed State Space (RSS)
  A. RSS in Human-Activity Recognition (HAR)

III. Experiment – Human-Humanoid Imitation
  A. Experiment Design
  B. Participants

III. Some Preliminary Results
  A. Timeseries of Accelerometer
  B. Reconstructed State Space

IV. Conclusions and Future Work

Outline

Movement Variability is not NOISE

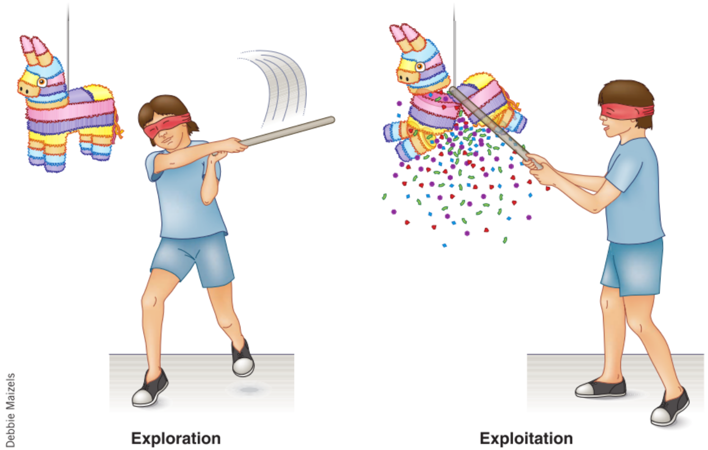


Figure 1: Find the piñata [Herzfeld and Shadmehr, 2014] .

Movement Variability

Movement Variability is an inherent feature that occurs not only within individual but also between individual systems of movement **[Newell and Corcos, 1993]** .

How to measure Movement Variability?

According to **[Preatoni et al., 2013]** , some nonlinear dynamics tools (dynamic invariants) can be used to explore the nature of movement variability and its relationship with skills development are:

- **Reconstructed State Space (RSS)**,
- Lyapunov Exponent.

Outline

Reconstructe State Space (RSS)

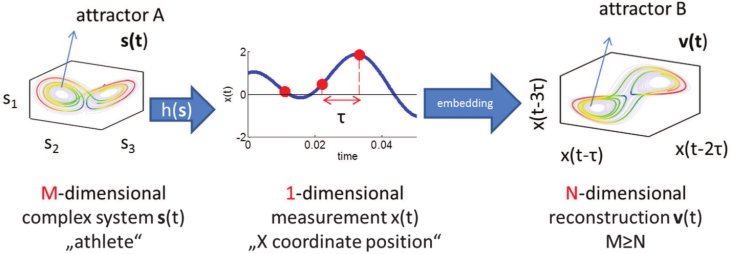


Figure 2: Reconstruction of a multidimensional attractor **[Quintana-Duque, 2012]** .

RSS in HAR

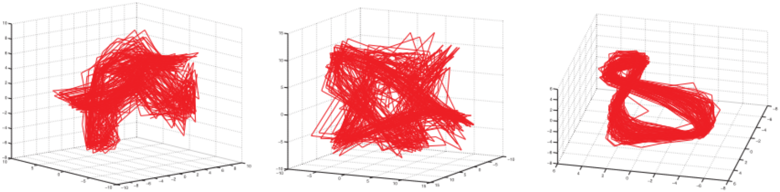


Figure 3: 3D Reconstructed State Spaces ($m = 3$, $\tau = 4$) for walking (left), running (middle), and cycling (right).
[Frank et al., 2010, Frank et al., 2012] .

RSS in HAR

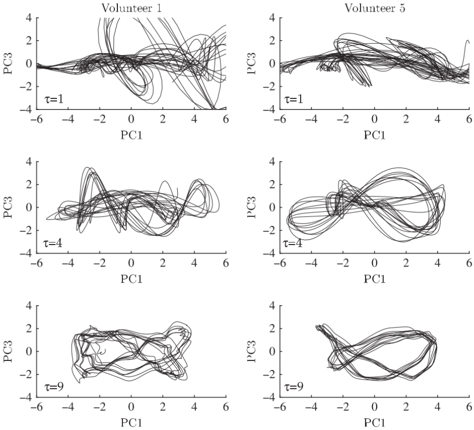


Figure 4: 2D Reconstructed State Spaces for gait patterns of two persons ($m = 20$ for $\tau = 1$, $\tau = 4$ and $\tau = 9$, respectively).
[Samà et al., 2013] .

How to build a ReconstructedStateSpace

For a given discrete time-series $x(n) = [x(1), x(2), \ldots, x(N)]$, a reconstructed state space can be created by

$$\overline{x}(n) = [x(n), x(n-\tau), x(n-2\tau), \ldots, x(n-(m-1)\tau)]$$

which creates a concatenated column-wise matrix of the time-delay versions of the original signal:

$$\mathbf{X} = \begin{pmatrix} x(1) & x(1-\tau) & x(1-2\tau) & \ldots & x(1-(m-1)\tau) \\ x(2) & x(2-\tau) & x(2-2\tau) & \ldots & x(2-(m-1)\tau) \\ \vdots & & & \ddots & \vdots \\ x(N) & x(N-\tau) & x(N-2\tau) & \ldots & x(N-(m-1)\tau) \end{pmatrix}$$

where m is the **embedding dimension** and τ is the **embedding delay** **[Takens, 1981]** .

Takens' Theorem

The Takens' Theorem states that for a large enough m is possible to unfold the attractor and $\tau > 0$ is chosen to maximize the information content of $x(n)$.

False Nearest Neighborhood and Mutual Information algorithms are used to compute the optimal value of m and τ. However, as pointed out by **[Samà et al., 2013]** the optimal values don't neccesarily represent the best rate of recognition.

RSS using PCA

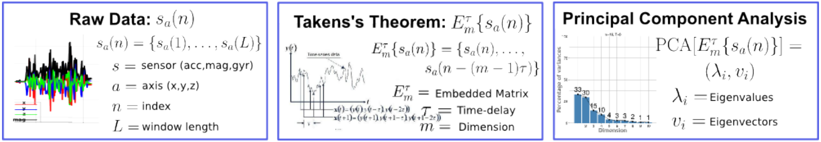
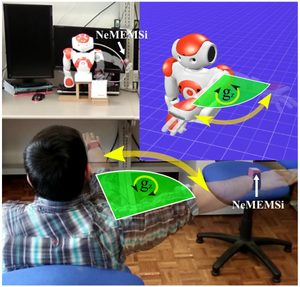


Figure 5: Framework to build the RSS

Outline

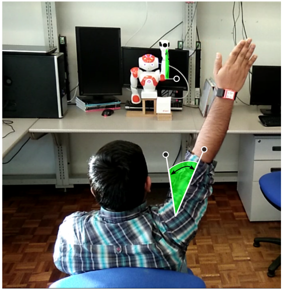
Experiment Design

HORIZONTAL



* HNormal
* HFaster

VERTICAL



* VNormal
* VFaster

Figure 6: Front-to-Front Human-Humanoid Imitation Using Wearable Inertial Sensors

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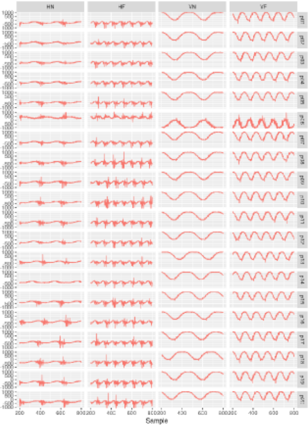
Participants

Twenty right-handed healthy participants (two females and ten males) with a mean age of 19.5$\pm$0.79 (from now on ab- breviated as p01 to p12) were invited to participate in this study.

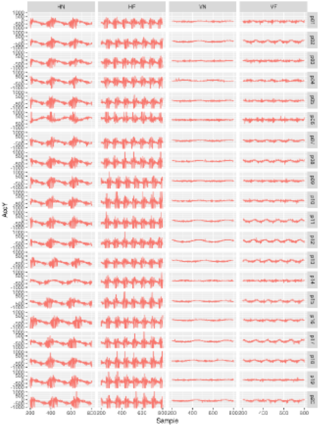
Outline

Raw Data from the Humanoid

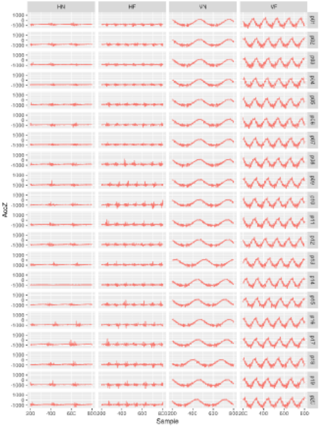
AccX



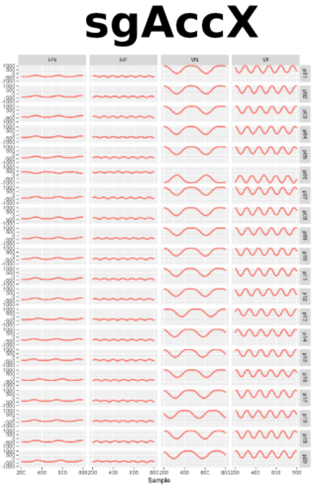
AccY

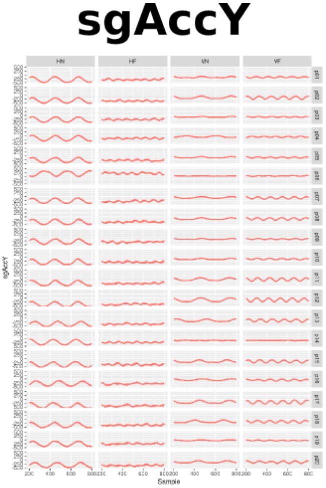


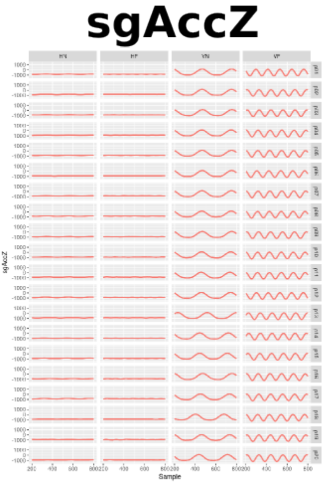
AccZ



Smoothed Data from the Humanoid

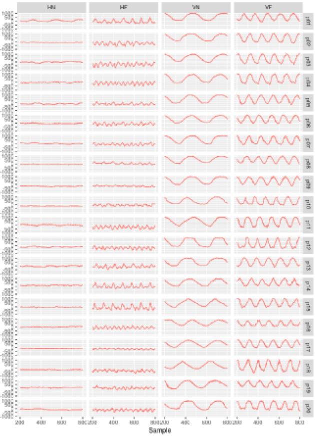




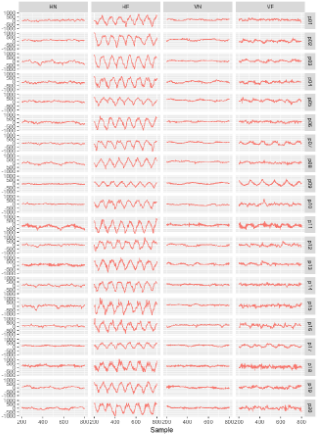


Raw Data from the Human

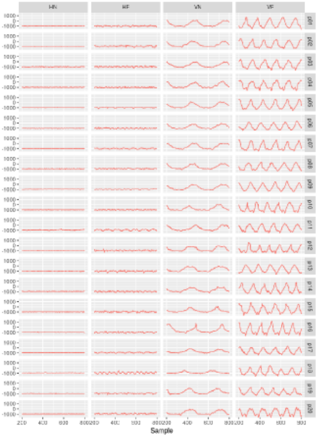
AccX



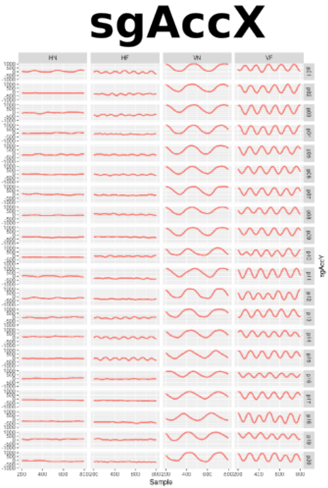
AccY

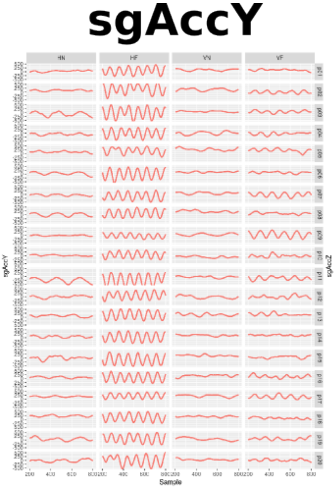


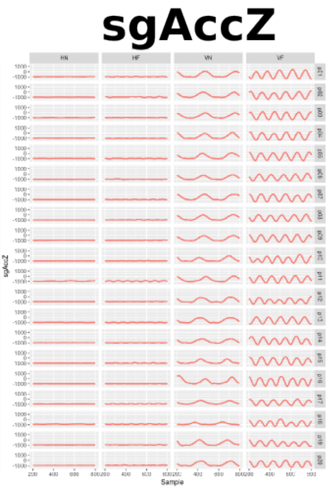
AccZ



Smoothed Data from the Human





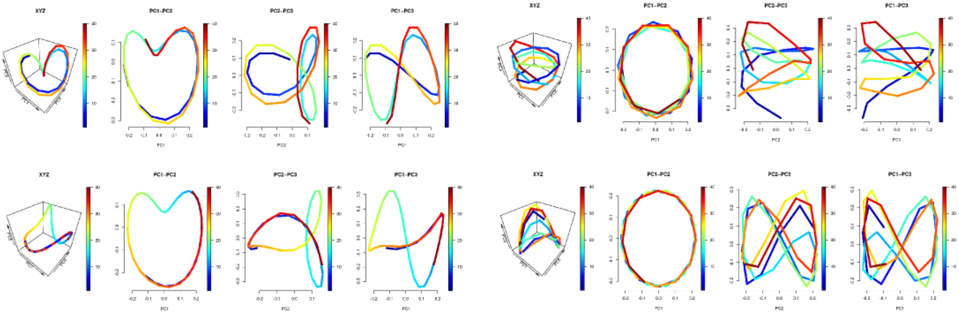


Outline

RSS for Humanoid trial01 sgAccX

RSS with $m = 40$, $\tau = 10$

HN **HF**

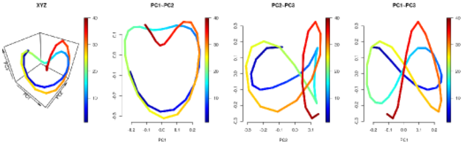


VN **VF**

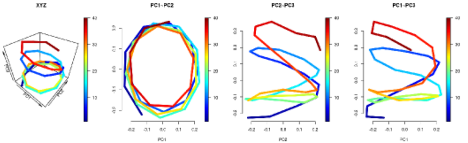
RSS for Humanoid trial10 sgAccX

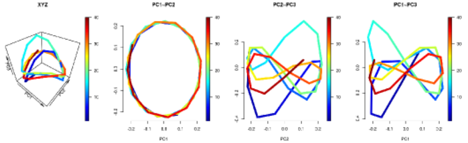
RSS with $m = 40$, $\tau = 10$

HN

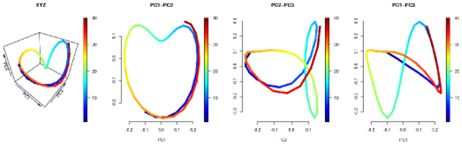


HF





VN

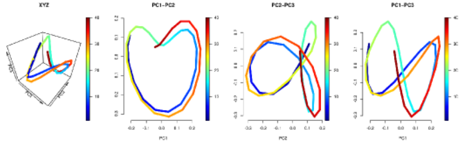


VF

RSS for Humanoid trial20 sgAccX

RSS with $m = 40$, $\tau = 10$

HN



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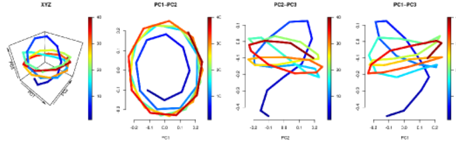

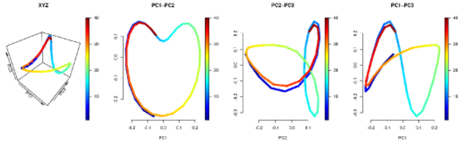

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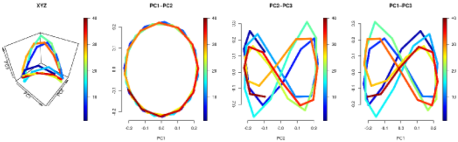

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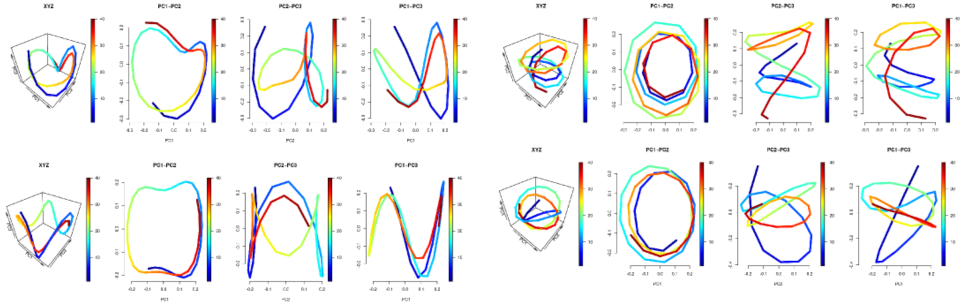
RSS for Human p01 sgAccX

RSS with $m = 40$, $\tau = 10$

HN

HF



VN

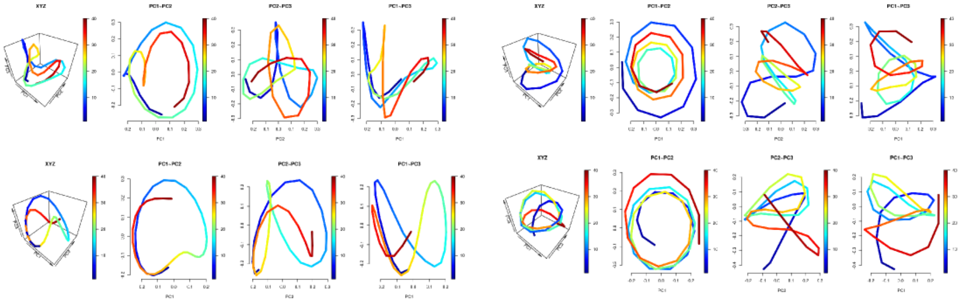
VF

RSS for Human p10 sgAccX

RSS with $m = 40$, $\tau = 10$

HN

HF



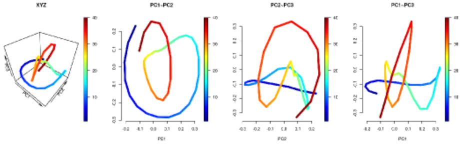
VN

VF

RSS for Human p20 sgAccX

RSS with $m = 40$, $\tau = 10$

HN



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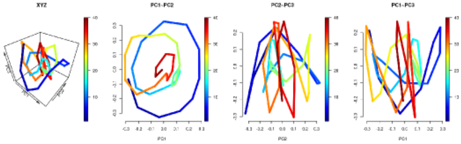

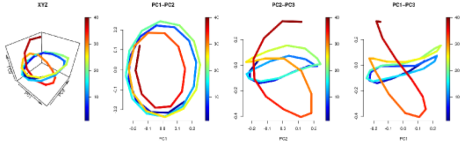

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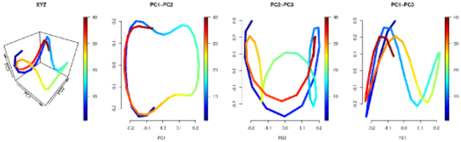
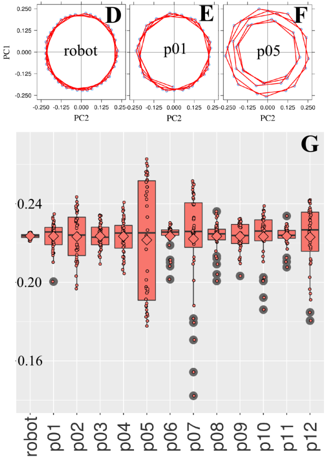


VF

Euclidean Distances in the RSS

RSS with $m = 40$, $\tau = 10$



Outline

Conclusions and Future Work

Pros and Cons of RSS

- (+) The RSS provide a visually a good representation of the variability of the activities.
- (-) The quality of the Euclidean distances in the RSS is debatable and needs further investigation.

TODO List:

- Have better understanding of the time-delay embedding theorem
- Implement the Lyapunov Exponent.
- Use Convolutional Neural Networks to classify Movement Variability

QUESTIONS?

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