

Towards the Quantification of Human-Robot Imitation Using Wearable Inertial Sensors

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Outline

I. Introduction

- A. Dancing with Markovito
- B. Movement Variability

II. Methods – Reconstructed State Space (RSS)

- A. RSS in Human-Activity Recognition (HAR)

III. Experiment – Human-Humanoid Imitation

- A. Experiment Design
- B. Participants

III. Preliminary Results

- A. Timeseries of the Accelerometer
- B. Reconstructed State Space

IV. Conclusions and Future Work

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Dancing Waltz with Markovito @ the Mexican Tournament of Robotics 2013

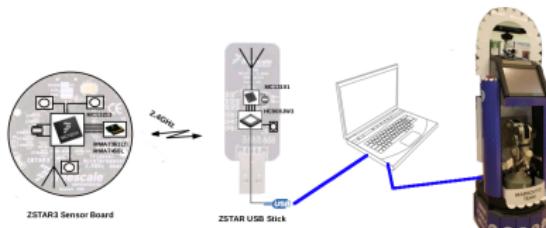


Figure 1: Human-Robot Interface

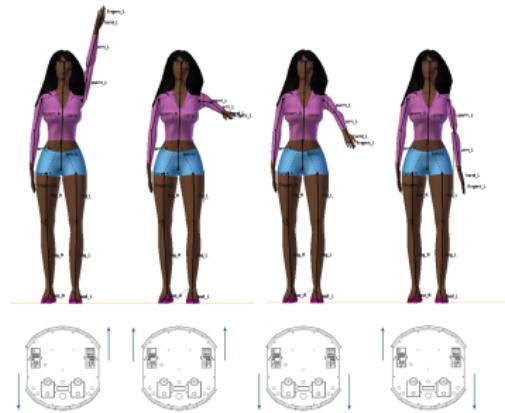


Figure 2: Human Body Gestures

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Movement Variability is not NOISE

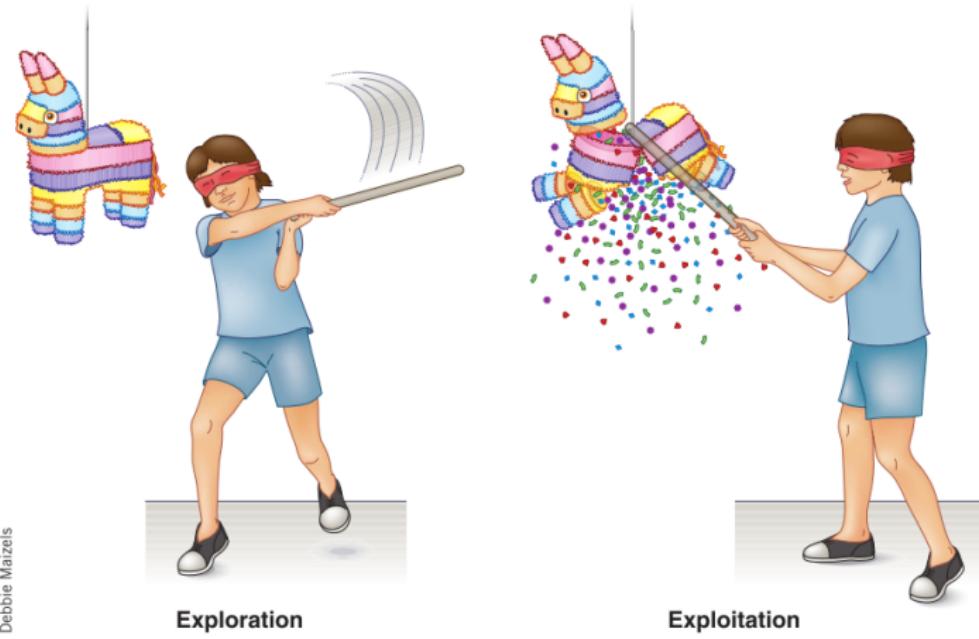


Figure 3: Find the piñata [Herzfeld and Shadmehr, 2014].

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 their relationship with skills development:

- Reconstructed State Space (RSS);
- Lyapunov Exponent.

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Reconstruct State Space (RSS)

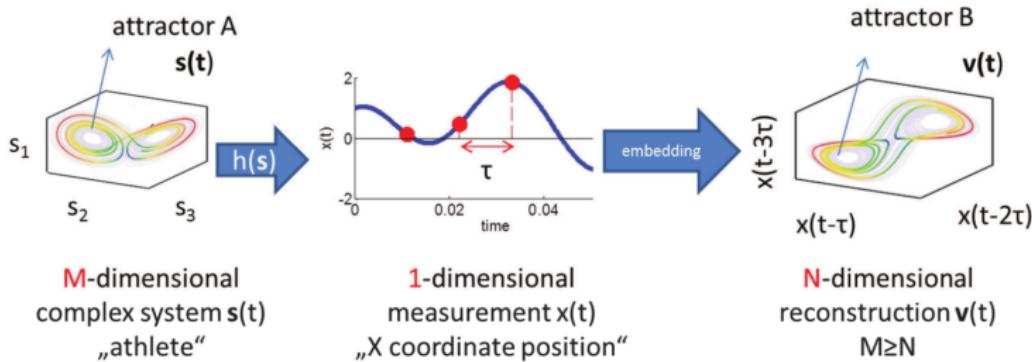


Figure 4: Reconstruction of a multidimensional attractor
[Quintana-Duque, 2012].

RSS in HAR

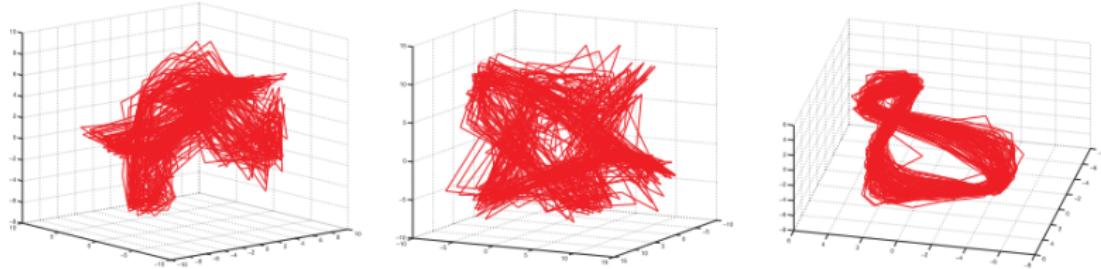


Figure 5: 3D Reconstructed State Spaces ($m = 3$, $\tau = 4$) for walking (left), running (middle), and cycling (right).

[Frank et al., 2010, Frank et al., 2012].

RSS in HAR

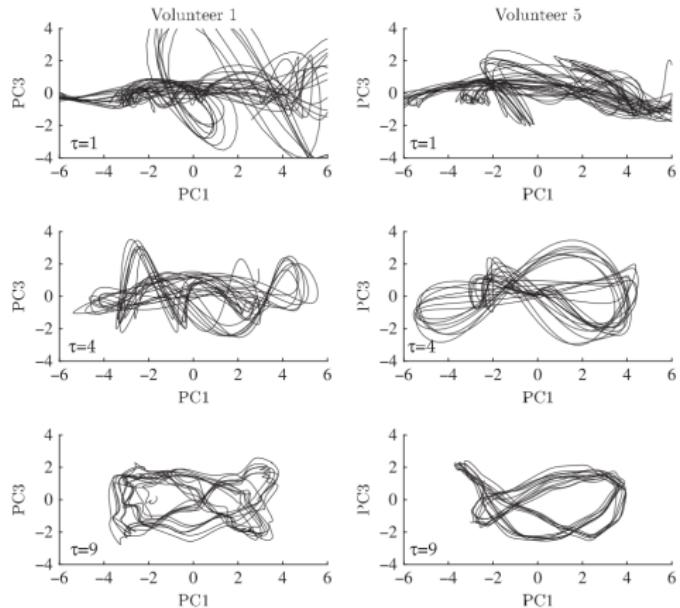


Figure 6: 2D Reconstructed State Spaces for gait patterns of two persons ($m = 20$ for $\tau = 1$, $\tau = 4$ and $\tau = 9$, respectively).
[Samà et al., 2013].

How to build the Reconstructed State Space

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

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

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

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

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 it 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 necessarily represent the best rate of recognition.

RSS using PCA

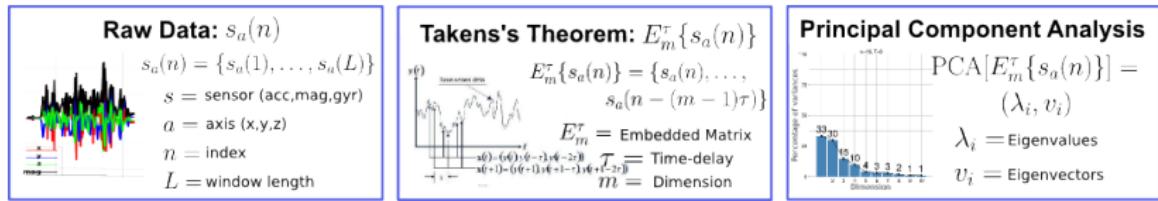


Figure 7: Framework to build the RSS

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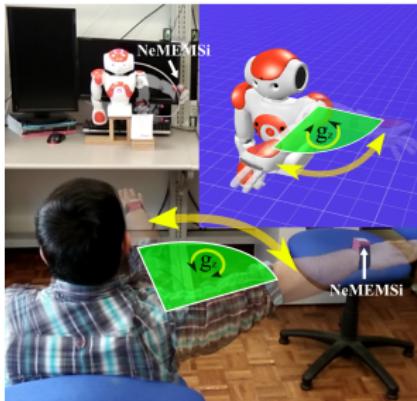
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Experiment Design

HORIZONTAL



* HNORMAL

* HFASTER

VERTICAL



* VNORMAL

* VFASTER

Figure 8: 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 ± 0.79 (abbreviated as p01 to p12) were invited to participate in this experiment.

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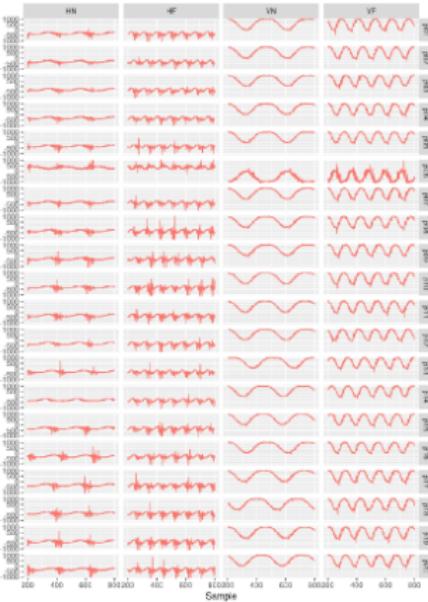
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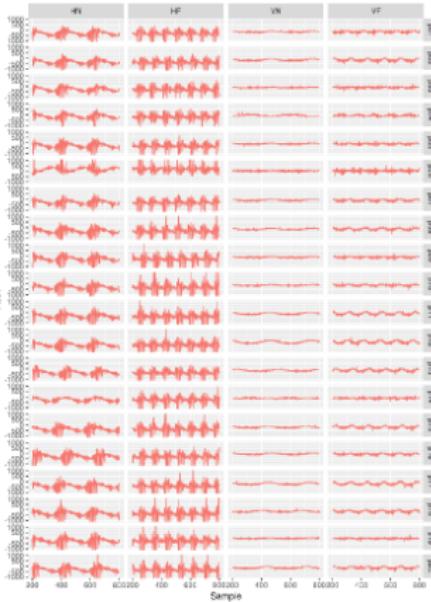
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Raw Data from NAO

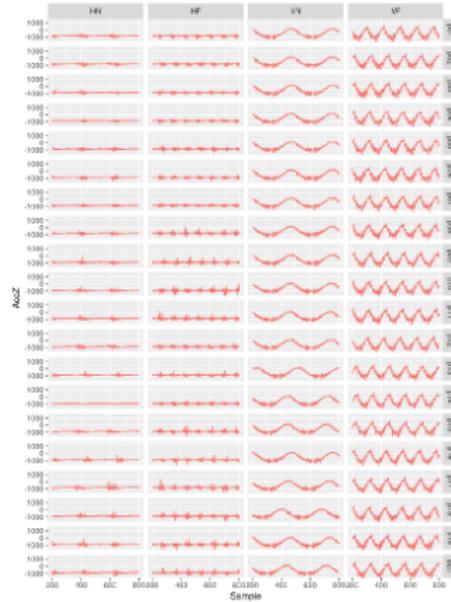
AccX



AccY

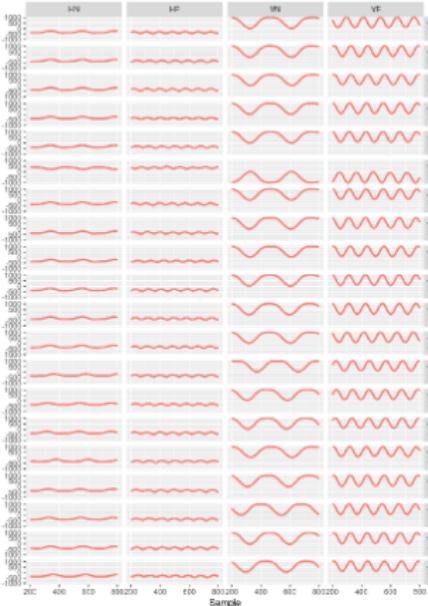


AccZ

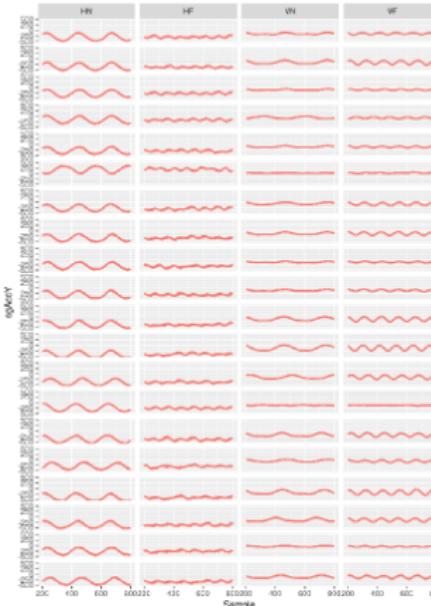


Smoothed Data from NAO

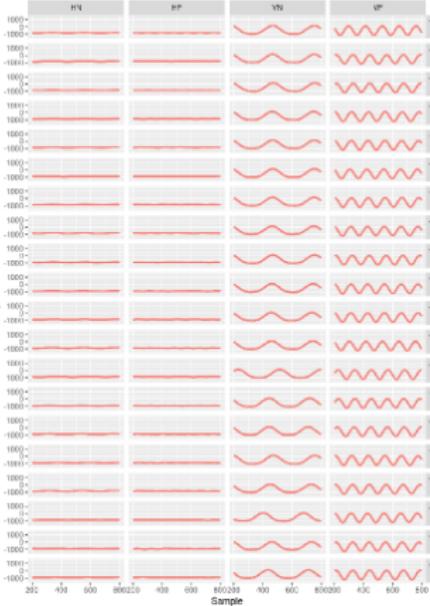
sgAccX



sgAccY

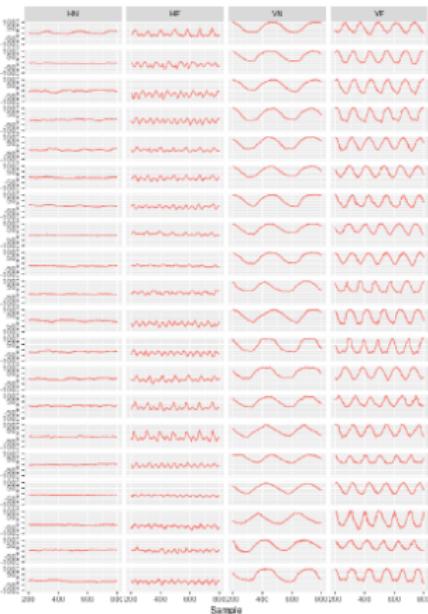


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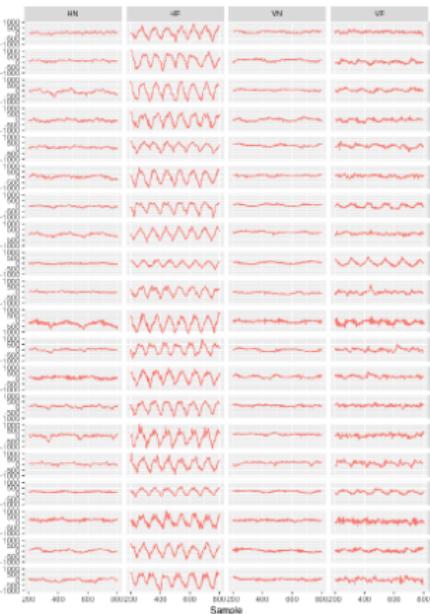


Raw Data from Participants

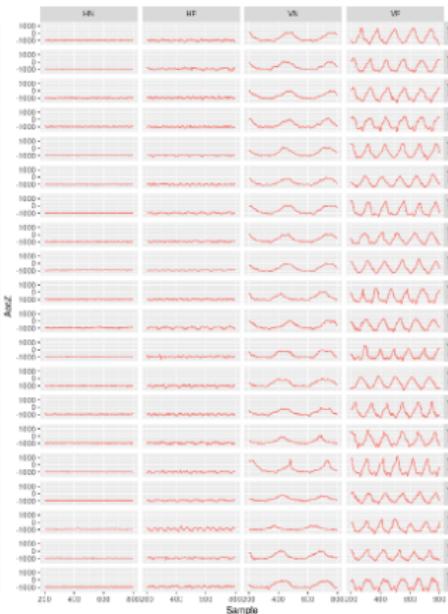
AccX



AccY

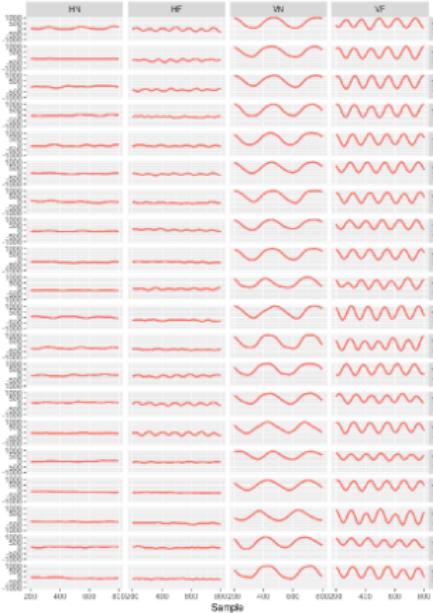


AccZ

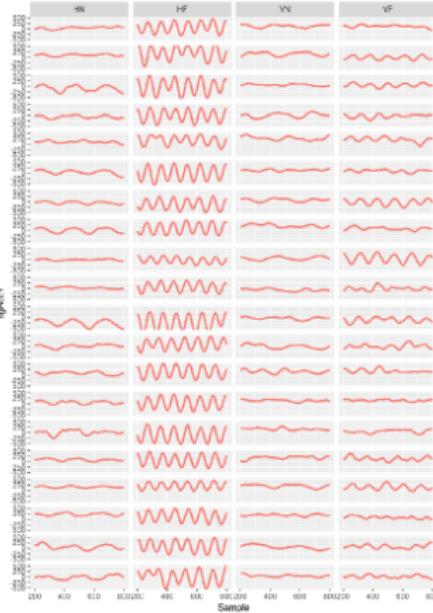


Smoothed Data from Participants

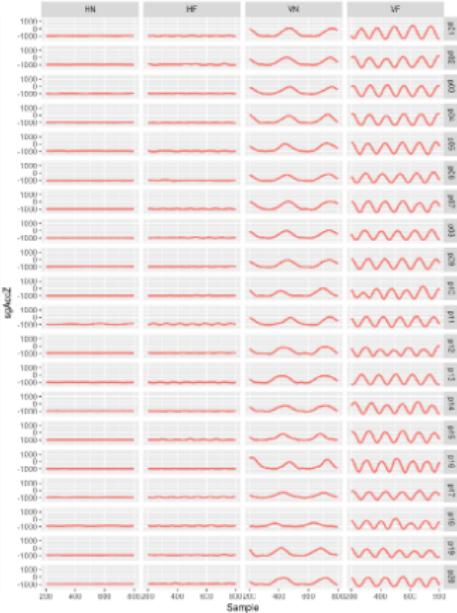
sgAccX



sgAccY



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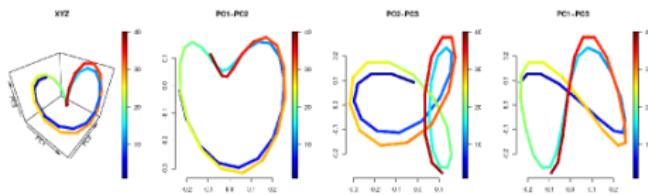
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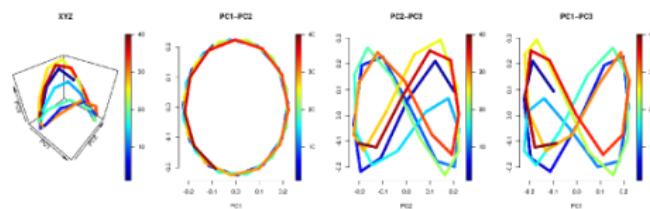
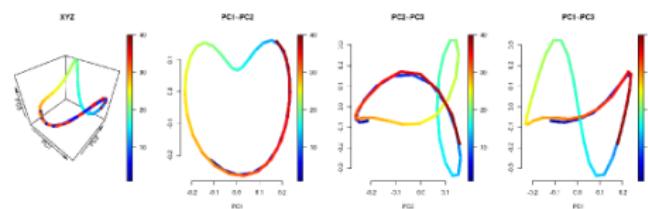
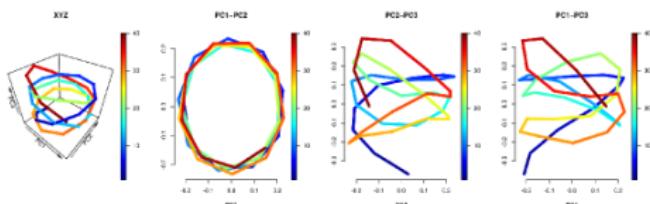
RSS for NAO TRIAL 01 (sgAccX)

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

HN



HF

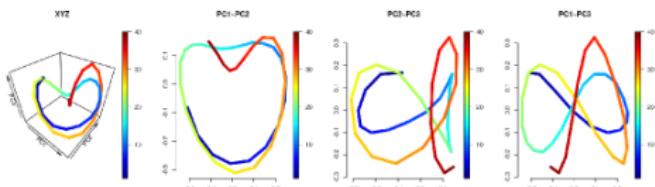


VN

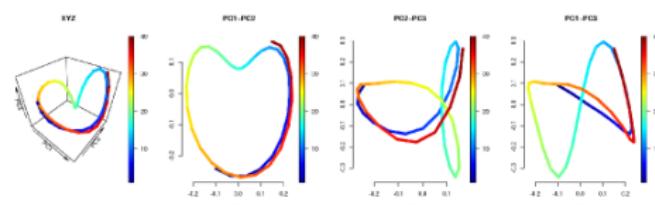
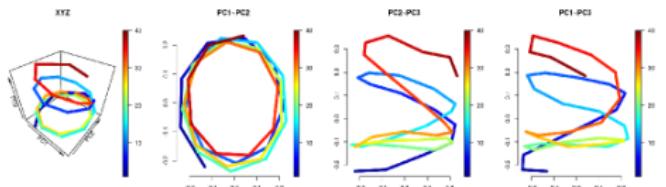
RSS for NAO TRIAL 10 (sgAccX)

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

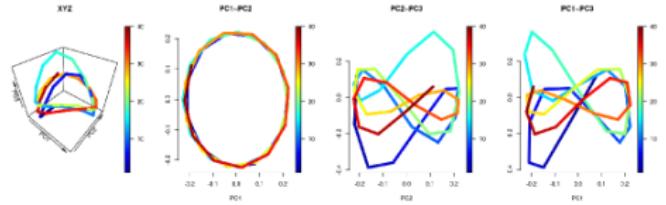
HN



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VN

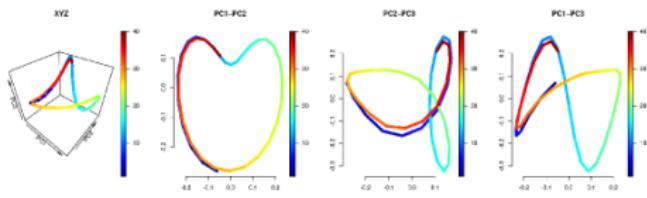
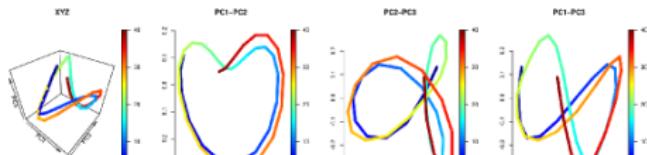


VF

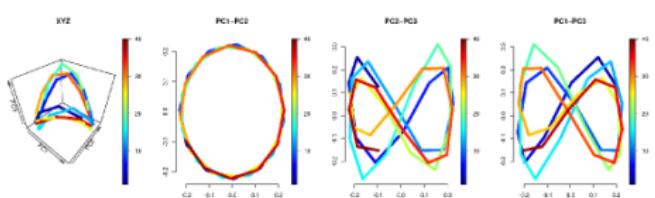
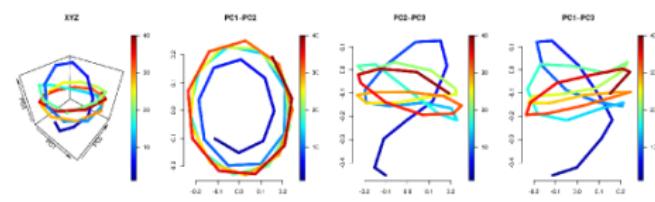
RSS for NAO TRIAL 20 (sgAccX)

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

HN



HF



VN

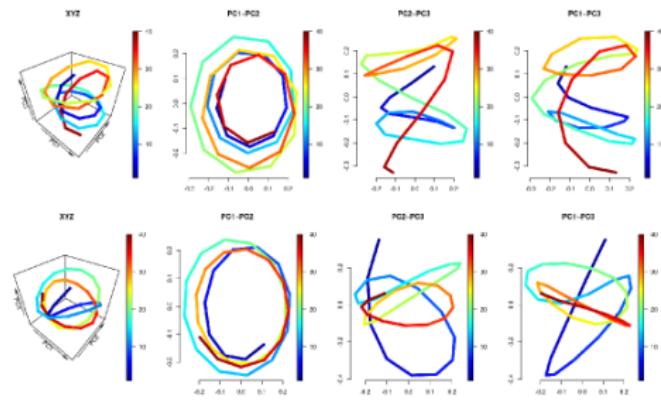
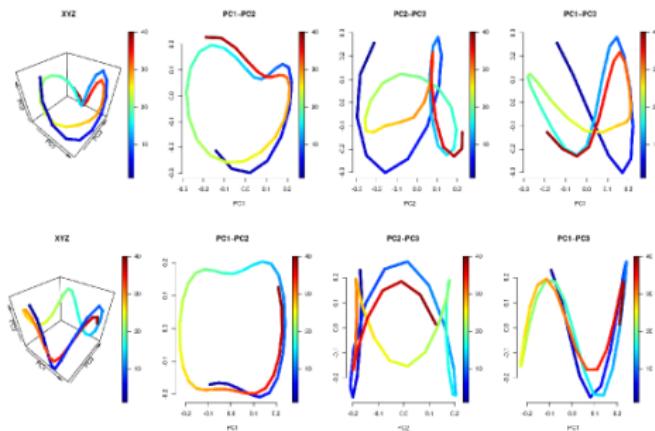
VF

RSS for P01 (sgAccX)

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

HN

HF



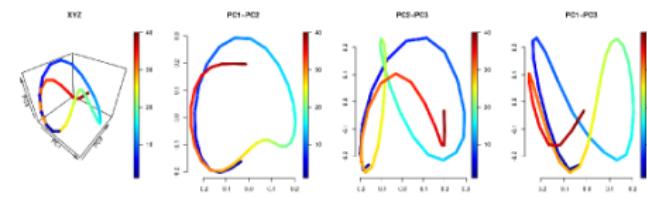
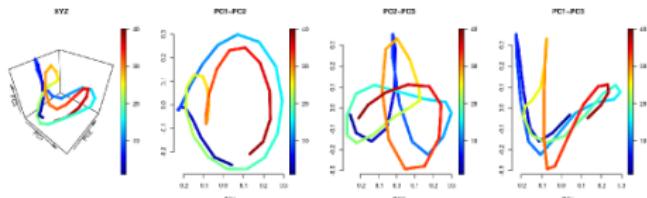
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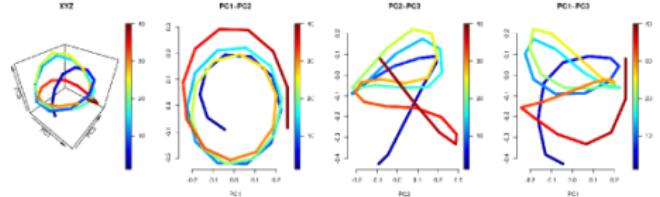
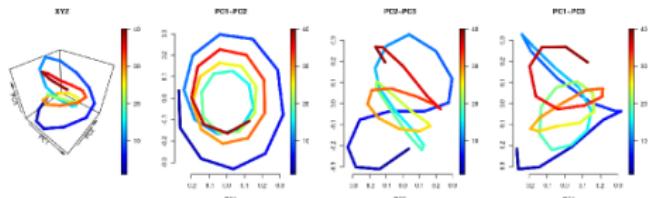
RSS for P10 (sgAccX)

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

HN



HF



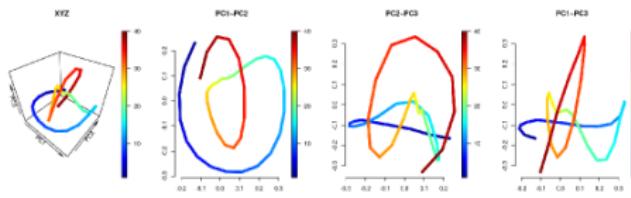
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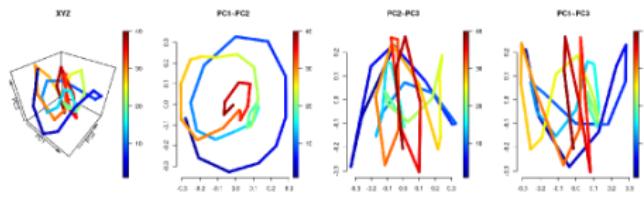
RSS for P20 (sgAccX)

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

HN



HF

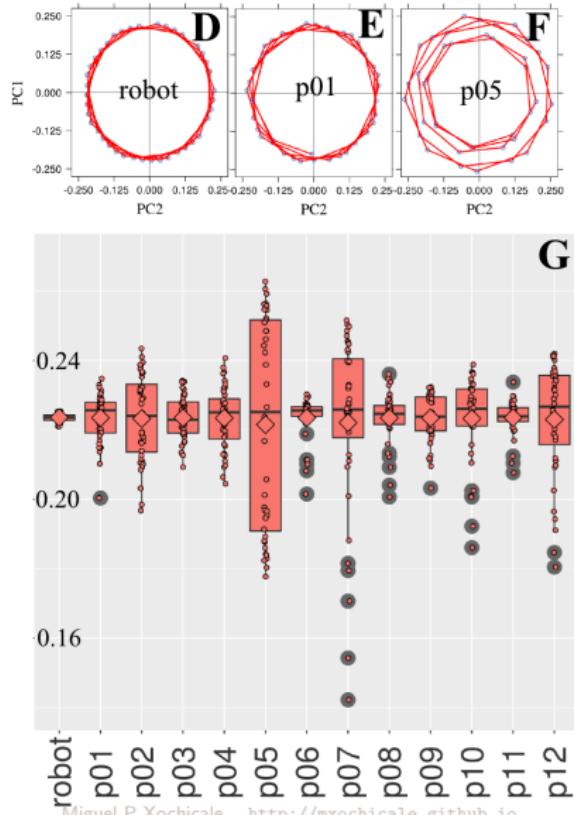


VN



VF

Euclidean Distances in the RSS ($m = 40$, $\tau = 10$)



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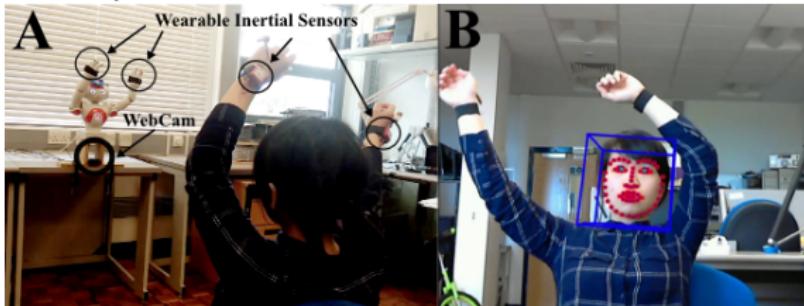
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Conclusions

- * It has been proposed a metric based on the Euclidean distances in the RSS to quantify how close a participant imitate NAO.
- * Pros and Cons of RSS
 - (+) The RSS provide a visually a good representation of the variability of the activities.
 - (-) The quality of the metric is debatable and needs further investigation.

Future Work for 2017-2018

- Provide an intuitive explanation of the dynamic invariants;
- Perform further experiments with participants of different: age, gender, state of health, and;
- Use Convolutional Neural Networks to classify Movement Variability
- Front to Front Human-Robot Imitation with Inertial Sensor and OpenFace Framework



QUESTIONS?

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<http://mxochicale.github.io/>

You can download the sources of this presentation here:

<https://github.com/mxochicale/PhD/tree/master/presentations/>



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