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UNIVERSITY OF
BIRMINGHAM

COLLEGE OF
ENGINEERING AND
PHYSICAL SCIENCES

Nonlinear Analysis to Quantify Movement Variability in Human-Humanoid Interaction

Presentation of my PhD VIVA

Birmingham, UK, 11 January 2019

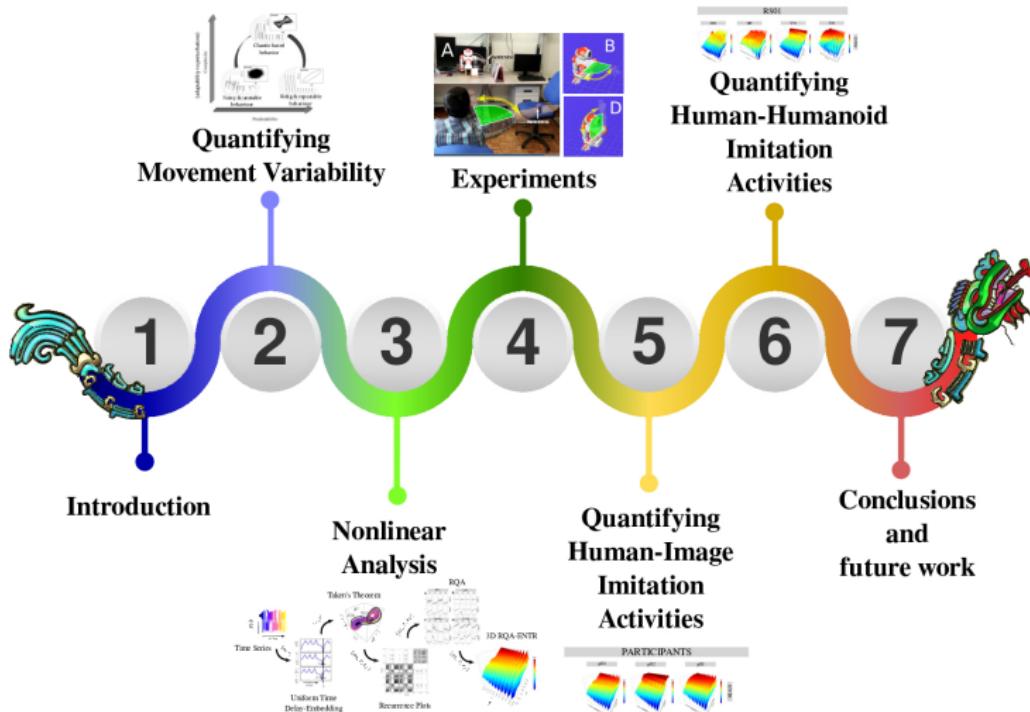
PhD Student: Miguel Xochicale

Primary supervisor: Chris Baber. **Secondary Supervisor:** Martin Russell

External Examiner: Max A. Little. **Internal Examiner:** Tim J. Jackson

School of Engineering
University of Birmingham, UK

Overview of the PhD thesis



MOVEMENT VARIABILITY

Why is challenging to investigate Human Movement Variability?

Human movement variability not only involves multiple joints and limbs for a specific task in a determined environment but also external information processed through all of our available senses and our prior experiences.

Modelling Movement Variability

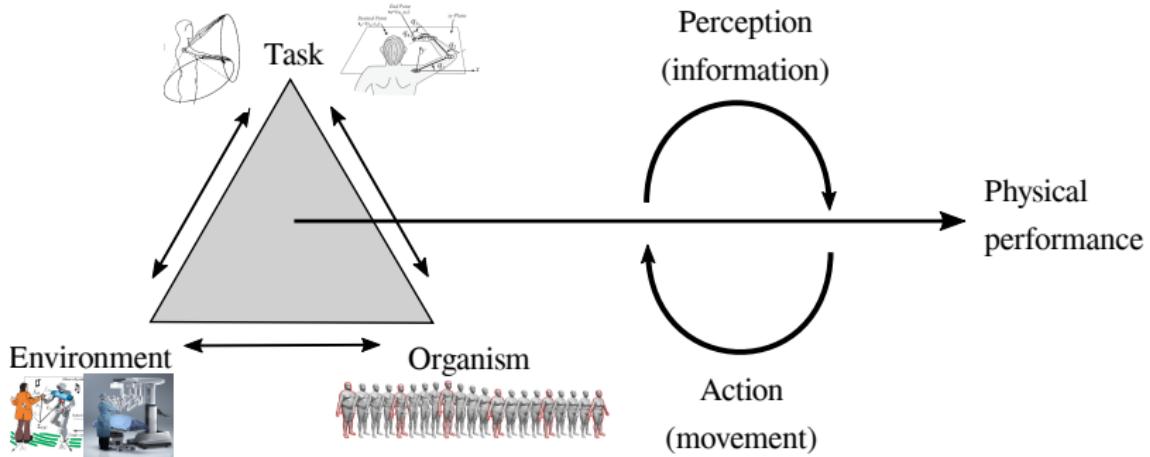


Figure 1: Newell's model of movement constrains

Modelling Movement Variability

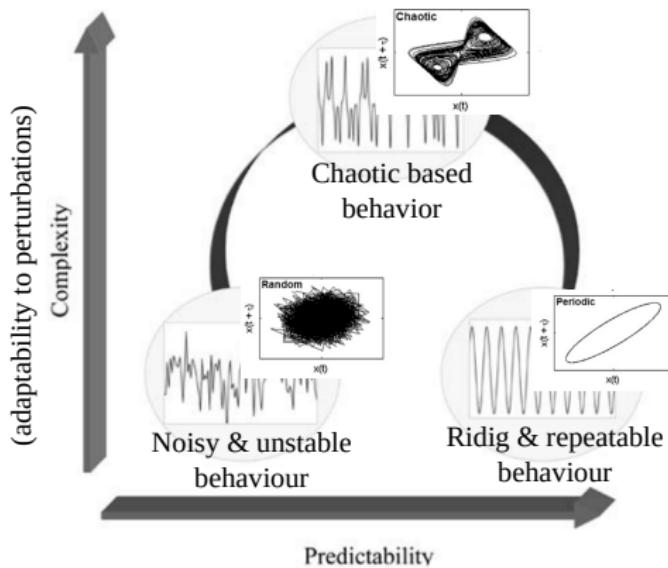


Figure 2: Theoretical Model of Optimal Movement Variability

Nonlinear Analysis

- Reconstructed State Space (Takens 1981)
 - Recurrence Plots (Eckmann et al. 1987, Marwan et al. 2007)
 - Approximate Entropy (Pincus 1991, 1995)
 - Sample Entropy (Richman and Moorman, 2000)
 - Largest Lyapunov exponent (Stergiou, 2016)
 - Recurrence Quantification Analysis (Zbilut and Webber et al., 1992)

There is no best tool to quantify MV and unification of tools is still an open question (Caballero et al. 2014; Wijnants et al. 2009) which led me (i) to explore different nonlinear analysis to measure MV and (ii) to understand their strengths and weaknesses.

Research Questions

- What are the effects on RSSs, RPs, and RQA metrics of different embedding parameters, different recurrence thresholds and different characteristics of time series (structure, smoothness and window length size)?
- What are the weaknesses and strengths of RQA metrics when quantifying movement variability?
- How does the smoothing of raw time series affect methods of nonlinear analysis when quantifying movement variability?

NONLINEAR ANALYSIS

State Space Reconstruction Theorem

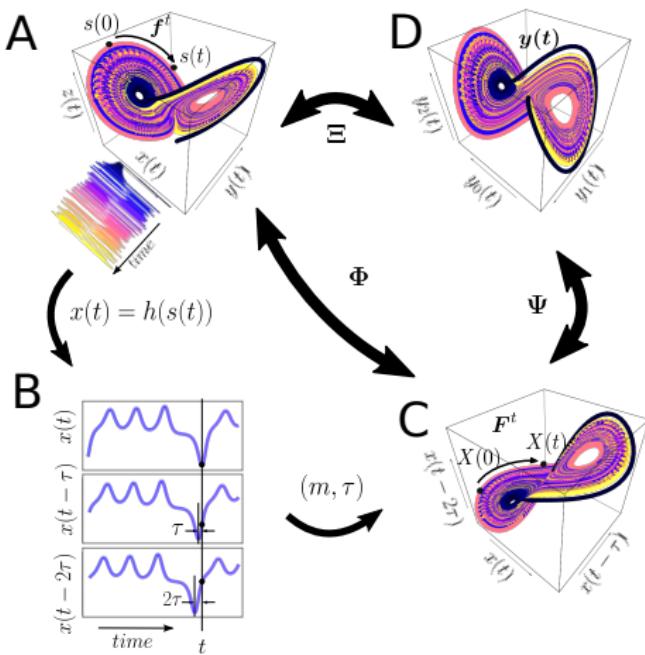


Figure is adapted from (Casdagli et al. 1991; Quintana-Duque (2012); Uzal et al. 2011)

Takens's Theorem

$$s(t) = f^t[s(0)]$$

- s represents a trajectory which evolves in an unknown d -dimensional manifold M
- f^t is a evolution function with time evolution t

Then

$$x(t) = h[s(t)]$$

- $x(t)$ scalar time series in \mathbb{R}
- h is a function defined on the trajectory $s(t)$

State Space Reconstruction Theorem

Uniform time-delay embedding matrix

$X(t) = \{x(t), x(t - \tau), \dots, x(t - (m-1)\tau)\}$ defines a map $\Phi : M \rightarrow \mathbb{R}^m$ such that

$$X(t) = \Phi(s(t))$$

where Φ is a diffeomorphic map whenever $\tau > 0$ and $m > 2d_{box}$ and d_{box} is the box-counting dimension of M .

Uniform Time-Delay Embedding (UTDE)

For a given discrete time series $\{x_n\}_{n=1}^N = [x_1, x_2, \dots, x_N]$ of sample length N , a uniform time-delay embedding matrix is defined as

$$\mathbf{X}_\tau^m = \begin{pmatrix} \tilde{x}_n \\ \tilde{x}_{n-\tau} \\ \vdots \\ \tilde{x}_{n-(m-1)\tau} \end{pmatrix}^T$$

where m is the **embedding dimension** and τ is the **embedding delay**.

The sample length for $\tilde{x}(n - i\tau)$, where $0 \leq i \leq (m - 1)$, is $N - (m - 1)\tau$, and the dimensions of \mathbf{X}_τ^m are $(m, (N - (m - 1)\tau))$.

Estimation of Embedding Parameters

False Nearest Neighbours (FNN) for m

Unfold the attractor (i.e. evolving trajectories in a state space).

Average Mutual Information (AMI) for τ

Maximize the information in the RSSs.

False Nearest Neighbours (FNN) for embedding dimension

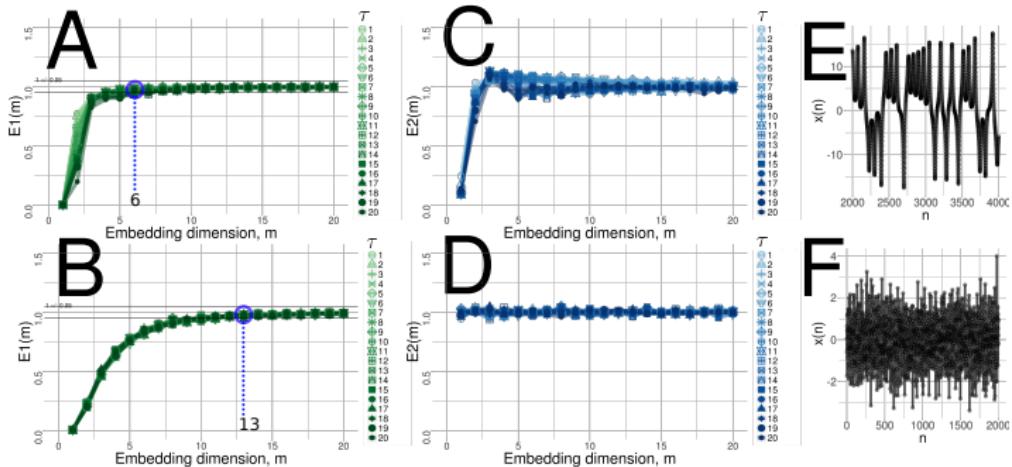


Figure is adapted from Cao L 1997 in *Physica D*

Figure 3: (A,B) $E_1(m)$ and (C, D) $E_2(m)$ values for (E) chaotic and (F) random time series

False Nearest Neighbours (FNN) for embedding dimension

False Nearest Neighbours (FNN)

$$E(m) = \frac{1}{N - m\tau} \sum_{i=1}^{N-m\tau} \frac{\|X_i(m+1) - X_{n(i,m)}(m+1)\|}{\|X_i(m) - X_{n(i,m)}(m)\|}$$

$E_1(m)$ and $E_2(m)$

$$E_1(m) = \frac{E(m+1)}{E(m)} \quad E_2(m) = \frac{E^*(m+1)}{E^*(m)}$$

Average Mutual Information (AMI) for embedding delay

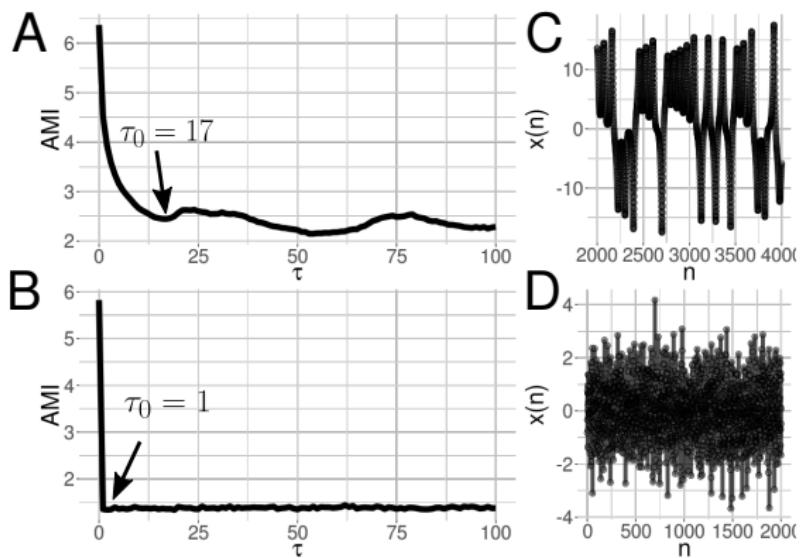


Figure is adapted from Kabiraj et al. 2012 in Chaos

Figure 4: (A, B) AMI values for (C) chaotic and (D) noise time series.

Average Mutual Information (AMI) for embedding delay

Average Mutual Information (AMI)

$$I(\tau) = \sum_{i,j}^N p_{ij} \log_2 \frac{p_{ij}}{p_i p_j}.$$

Recurrence Plot (RP)

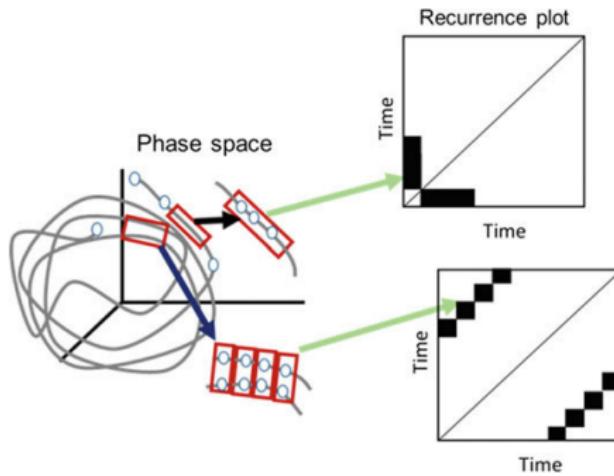


Figure is from Pawar 2018.

Figure 5: The vertical lines in the RP show that more than one point of the same trajectory are recurring at the same time. The diagonal lines in the RP depict that two trajectories are running in parallel to each other.

Recurrence Plot

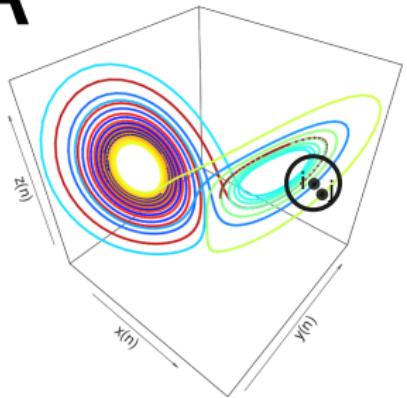
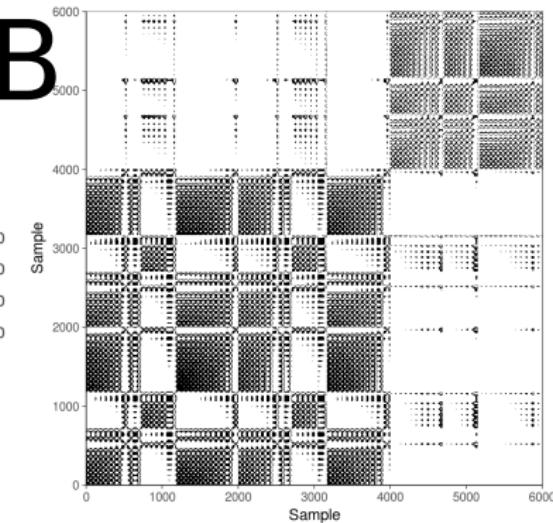
A**B**

Figure is adapted from (Marwan et al. 2007)

Figure 6: (A) State space for Lorenz systems, and (B) Recurrence plot with embeddings ($m = 1$, $\tau = 1$) and $\epsilon = 5$

Recurrence Plots

$\mathbf{R}_{i,j}^m(\epsilon)$ is two dimensional plot of $N \times N$ square matrix defined by

$$\mathbf{R}_{i,j}^m(\epsilon) = \Theta(\epsilon_i - \|X(i) - X(j)\|), \quad i, j = 1, \dots, N$$

where N is the number of considered reconstructed states of $X(i)$ ($X(i) \in \mathbb{R}^m$), ϵ is a threshold distance, $\|\cdot\|$ a norm, and $\Theta(\cdot)$ is the Heaviside function.

Recurrence Plot Patterns

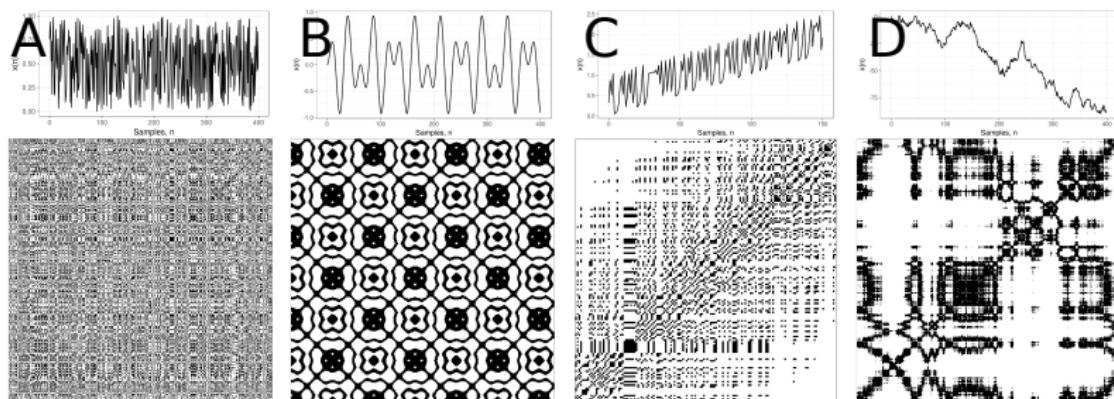


Figure is adapted from (Marwan et al. 2007)

Figure 7: Recurrence plots for (A) uniformly distributed noise, (B) super-positioned harmonic oscillation, (C) drift logistic map with a linear increase term, and (D) disrupted brownian motion.

Recurrence Quantification Analysis (RQA)

REC enumerates the black dots in the RP.

$$REC(\epsilon, N) = \frac{1}{N^2 - N} \sum_{i \neq j=1}^N \mathbf{R}_{i,j}^m(\epsilon)$$

DET fraction of recurrence points that form diagonal lines.
(interpreted as the predictability where, for example, periodic signals show longer diagonal lines than chaotic ones.)

$$DET = \frac{\sum_{l=d_{min}}^N lH_D l}{\sum_{i,j=1}^N \mathbf{R}_{i,j}^m(\epsilon)}$$

Recurrence Quantification Analysis (RQA)

RATIO is the ratio of DET to REC.

(useful to discover dynamic transitions).

ENTR Shannon entropy of the frequency distribution of the diagonal line lengths. (*useful to represent the complexity of the structure of the time series*)

$$ENT = - \sum_{l=d_{min}}^N p(l) \ln p(l),$$

where

$$p(l) = \frac{H_D(l)}{\sum_{l=d_{min}}^N H_D(l)}$$

3D surface plots of RQA

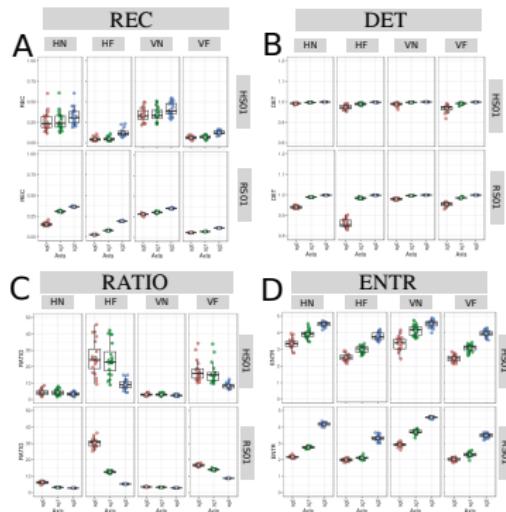


Figure is adapted from Xochicale 2019

Figure 8: Recurrence Quantification Analysis with $m_0 = 6$, $\tau_0 = 8$ and $\epsilon = 1$.

3D surface plots of RQA

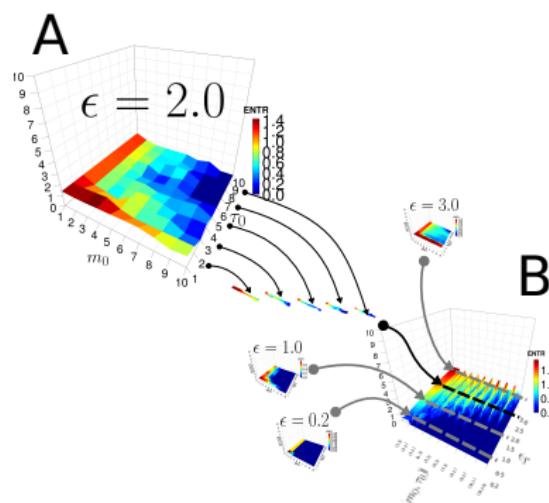


Figure is adapted from Xochicale 2019

Figure 9: (A) 3D surface plots for with increasing pair of embedding parameters ($0 \leq m \leq 10$, $0 \leq \tau \leq 10$) and $\epsilon = 3.0$. (B) Surface plot A with decimal increase of 0.1 for recurrence thresholds ($0.2 \geq \epsilon \leq 3$).

3D surface plots of RQA

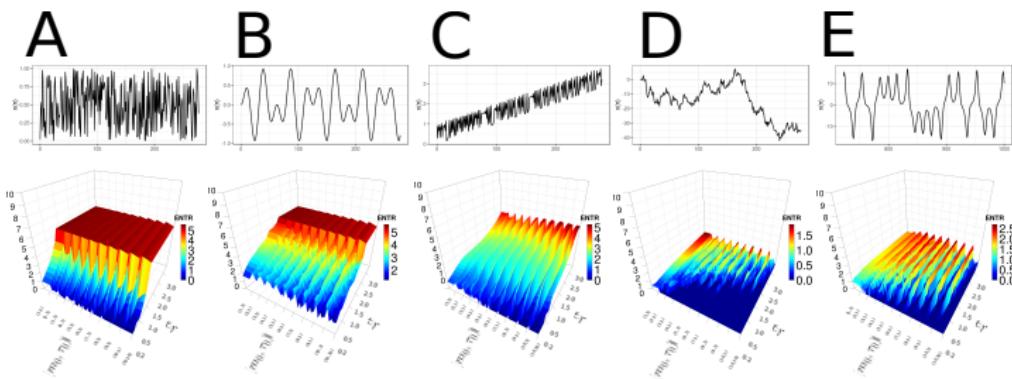


Figure is adapted from Xochicale 2019

Figure 10: 3D surface plots for (A) uniformly distributed noise, (B) super-positionet harmonic oscillation, (C) drift logistic map with a linear increase term, (D) disrupted brownian motion, and (E) Lorenz system.

EXPERIMENT

Participants

Originally, 23 right-handed healthy participants were invited for two experiments, however some of these were not considered in the analysis due to technical problems with IMU's.

Human-Image Imitation Activity

6 participants ($p01, p04, p05, p10, p11, p15$) with mean and standard deviation (SD) age of mean=19.5 (SD=0.83) years.

Human-Humanoid Imitation Activity

20 participants with mean and standard deviation (SD) age of mean=19.8 (SD=1.39) years, being four females and sixteen males.

Human-Image Imitation Activities

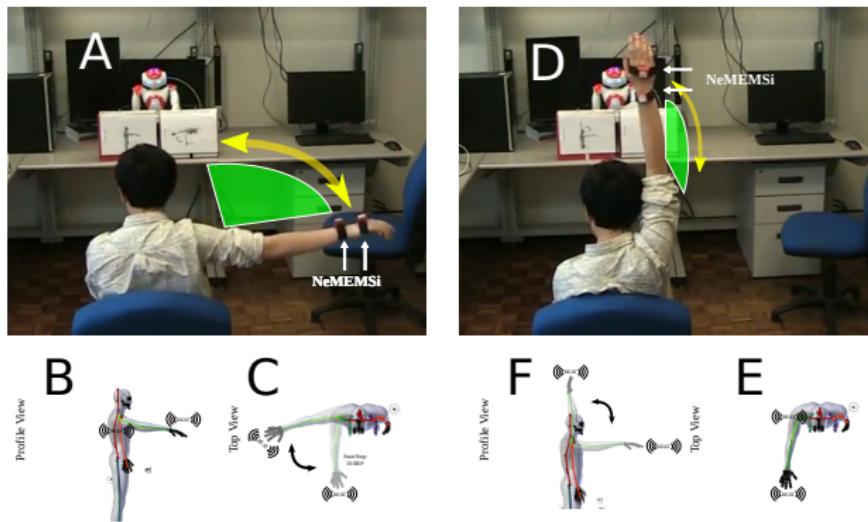


Figure 11: Human-Image Imitation Activities of Arm Movements for two speed conditions: Horizontal Normal (HN) and Horizontal Faster (HF).

Human-Humanoid Imitation Activities

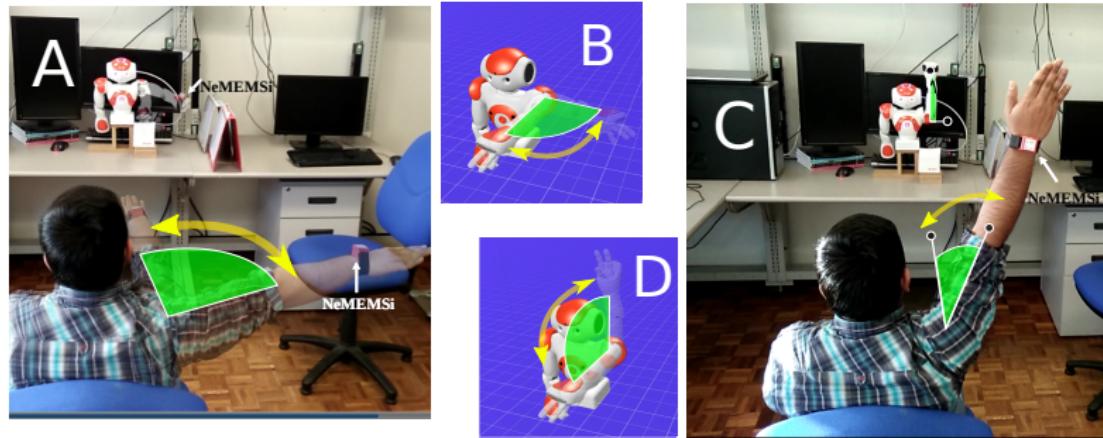


Figure 12: (A/C) Front-to-Front Human-Humanoid Imitation Activities of Horizontal/Vertical Movements, (B/D) NAO, humanoid robot, performing Horizontal/Vertical arm movements.

RESULTS

From Raw to Smoothed Time Series

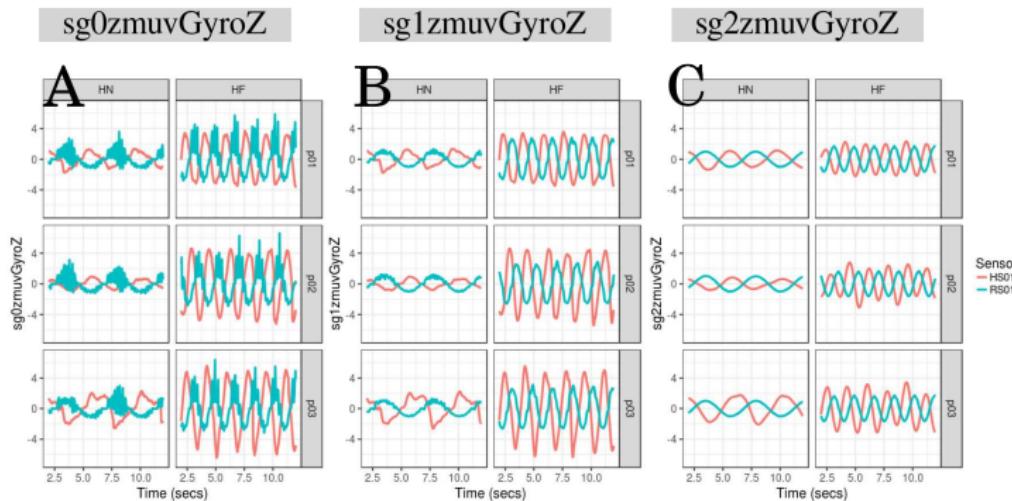


Figure 13: Time-series of horizontal movements for (A) normalised, (B) sgolay($p=5, n=25$), and (C) sgolay($p=5, n=159$).

From Raw to Smoothed Time Series

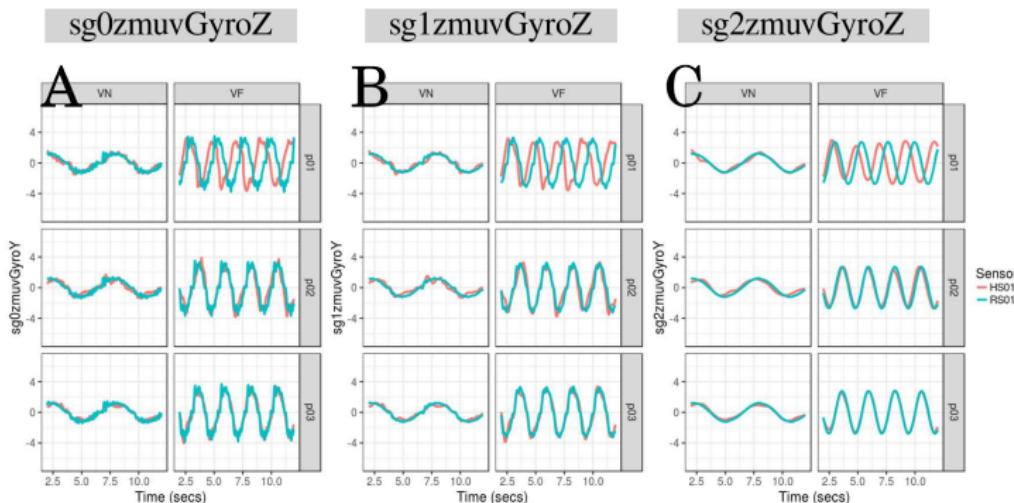


Figure 14: Time-series of vertical movements for (A) normalised, (B) sgolay($p=5, n=25$), and (C) sgolay($p=5, n=159$).

Minimum Embedding Parameters

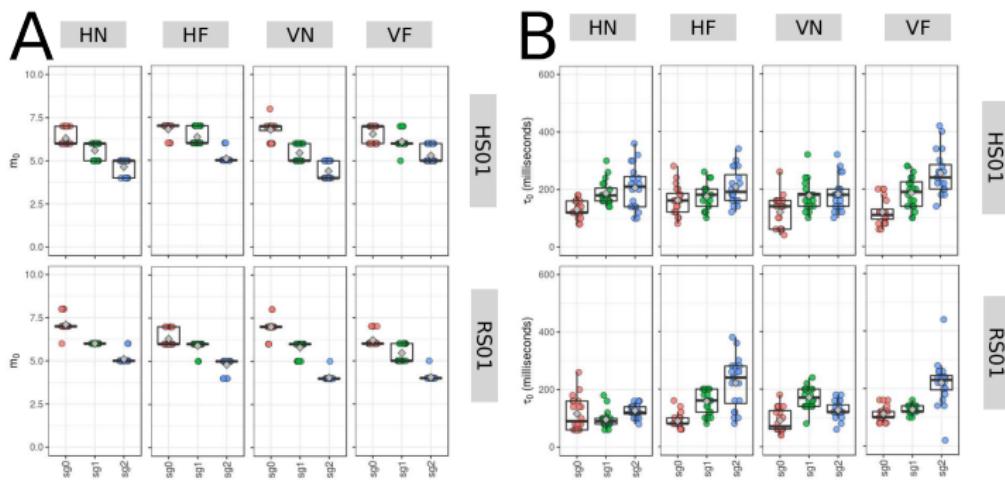


Figure 15: (A) Minimum Embedding Dimension (B) First Minimum AMI

Reconstructed State Spaces

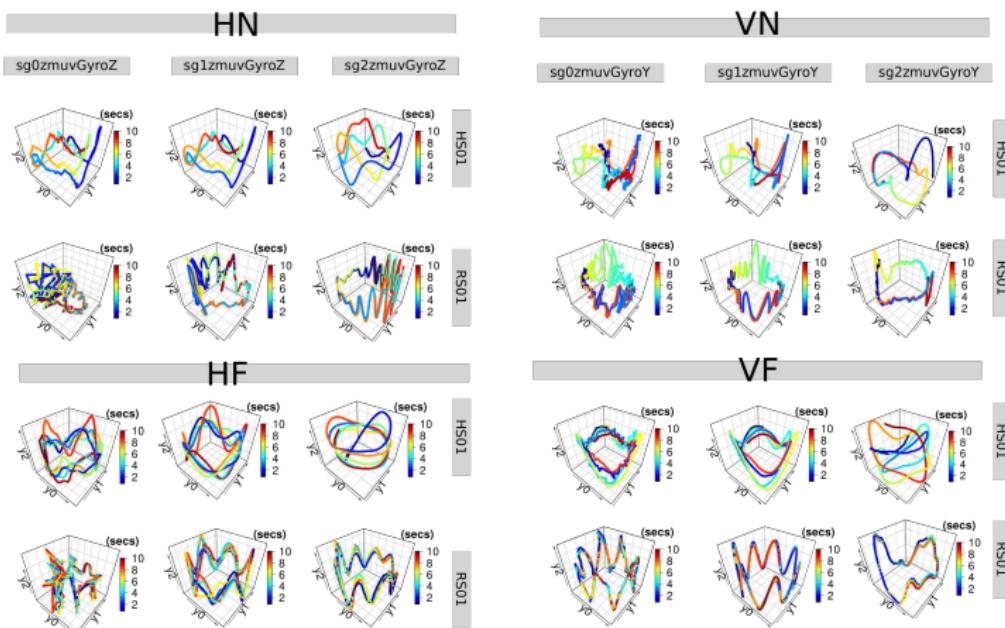


Figure 16: RSS for participant 01 computed with ($m = 6$, $\tau = 8$) for different activities, signals and source of time-series data.

Recurrence Plots

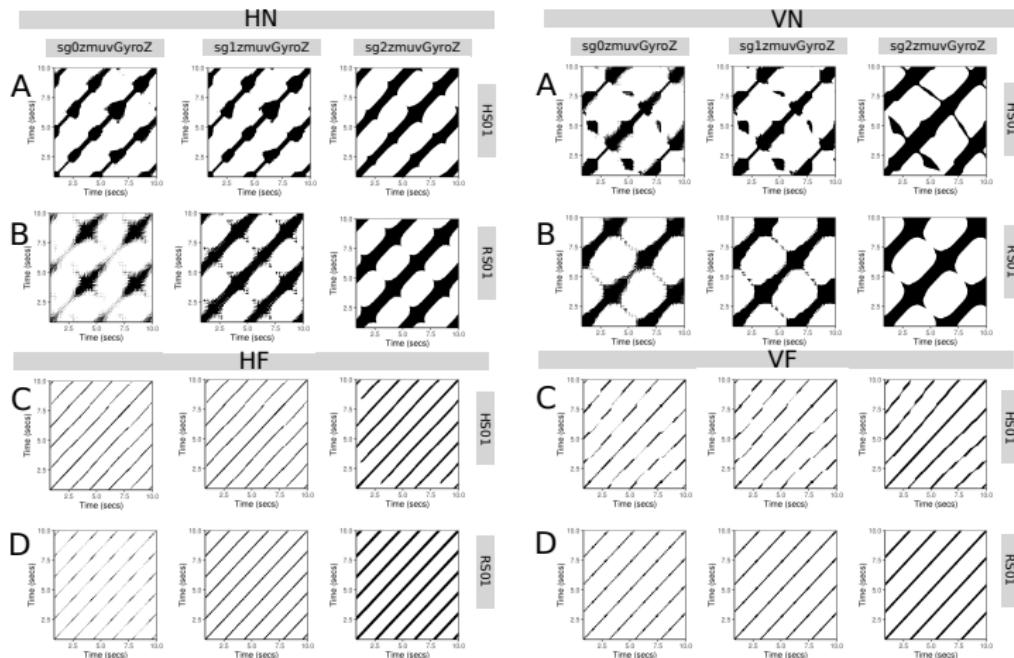


Figure 17: RP for participant 01 computed with ($m = 6$, $\tau = 8$, $\epsilon = 1$) for different activities, signals and source of time-series data.

Recurrence Quantification Analysis

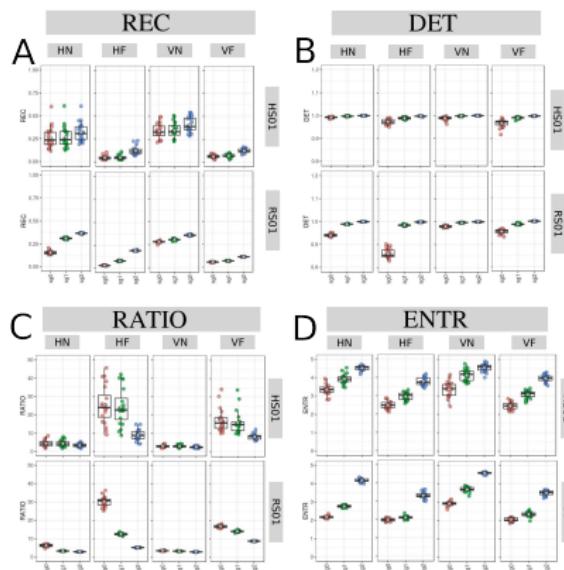


Figure 18: Box values of RQA computed with ($m = 7$, $\tau = 5$, $\epsilon = 1$). These values are for 20 participants.

3D surfaces plots of RQA

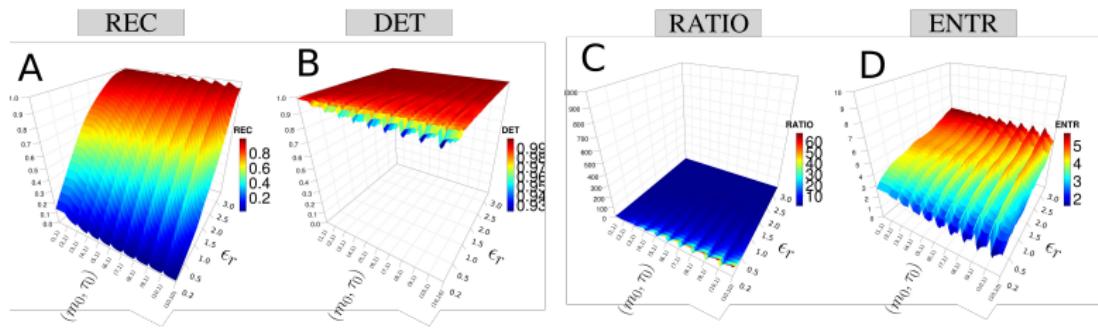


Figure 19: 3D RQA surfaces with increasing pair of embedding parameters ($0 \leq m \leq 10$, $0 \leq \tau \leq 10$) and recurrence thresholds ($0.2 \leq \epsilon \leq 3$).

Sensors and activities

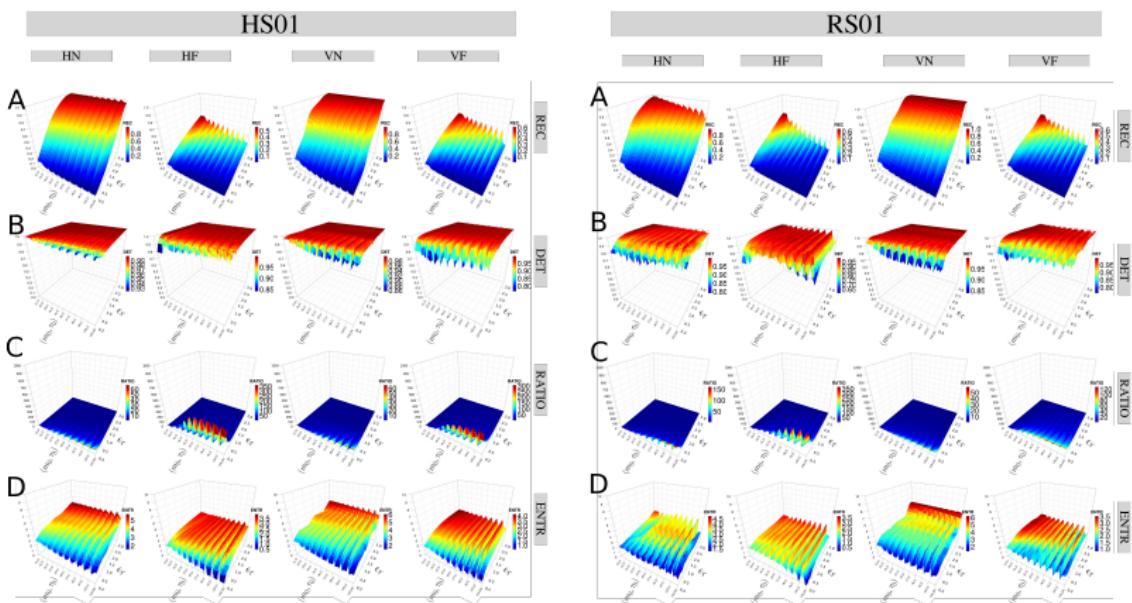


Figure 20: 3D surface plots of RQA for different sensors and activities.

Window size lengths

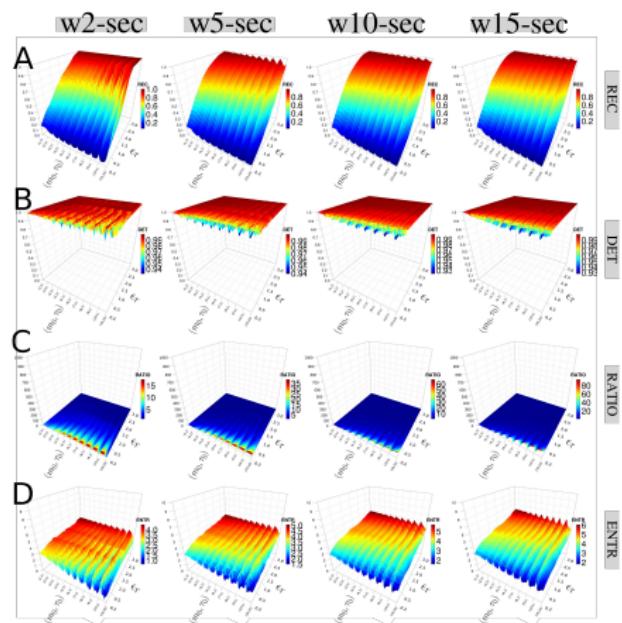


Figure 21: Window length size effect on 3D surface plots of RQA.

Smoothness

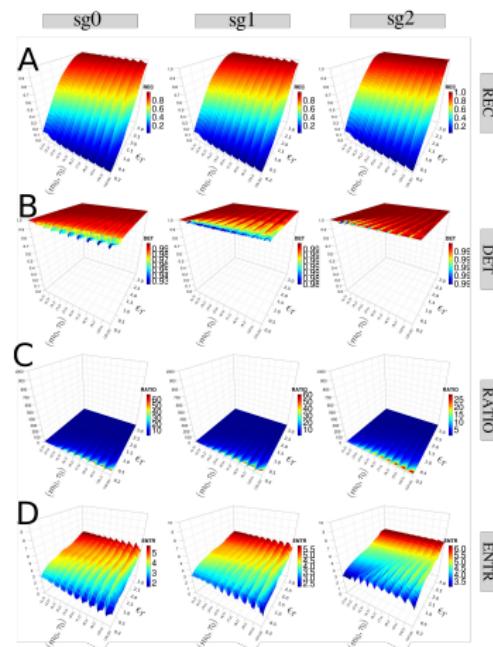


Figure 22: Smoothness effect on 3D surface plots of RQA.

Participants

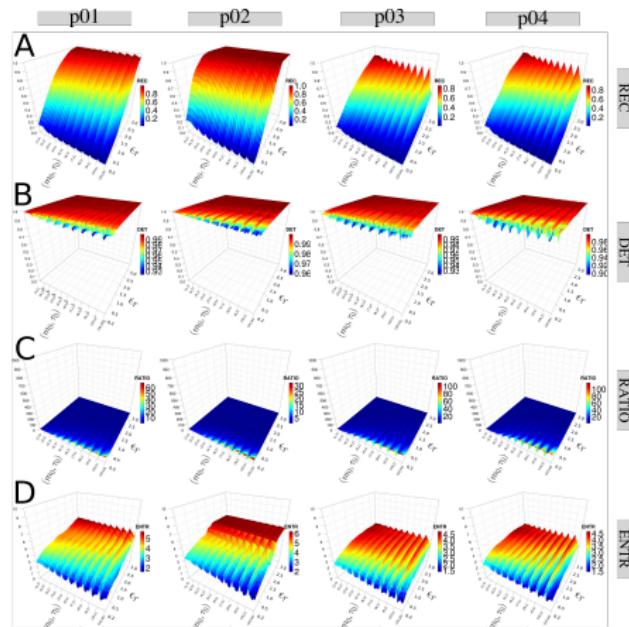


Figure 23: Participants differences of 3D surface plots of RQA.

CONCLUSIONS

Research Questions

- **Q1: What are the effects on RSSs, RPs, and RQA metrics of different embedding parameters, different recurrence thresholds and different characteristics of time series (structure, smoothness and window length size)?**

The impact on nonlinear analysis tools is evidently for different data time-series. That said, the main contribution of this thesis is finding that measurements of entropy using 3D plot surfaces of RQA appear to be robust to real-word data (i.e. different time series structures, window length size and levels of smoothness).

Research Questions

- **Q2: What are the weaknesses and strengths of RQA metrics when quantifying movement variability?**

WEAKNESSES: (i) requirement of an expert for interpretation and computation of nonlinear analysis results, (ii) laborious implementation, and (iii) nonlinear analysis does not give the best representation of the dynamics of time-series data.

STRENGTHS: (i) little setup of parameters for 3D plot surfaces, and (ii) 3D plot surfaces can provide insight into the understanding of the dynamics of time-series data.

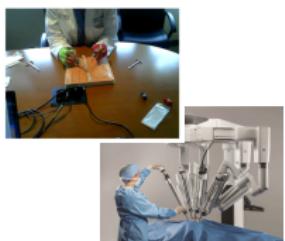
Research Questions

- **Q3: How does the smoothing of raw time series affect methods of nonlinear analysis when quantifying movement variability?**

Smoothing raw time series can create well defined trajectories or patterns in RSS or RP, however such increase of smoothness can also create more complex (i.e. not well defined) trajectories or patterns in nonlinear analysis.

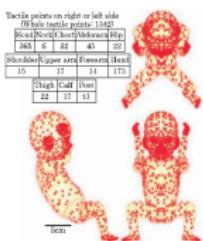
Applications of Nonlinear Dynamics

Quantification of skill learning



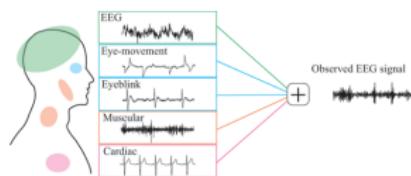
- * Surgical Skills Assessment
- * Robot-Assisted Surgery

Fetal behavioral development



- * General movements
- * Arm/Legs Movs
- * Hand/Face Contacts

Nonlinear Biomedical Signal Processing



- * EEG time series
- * Heart rate variability
- * Eye Movements

Future Work

Investigate

- other derivatives of acceleration data to have better understanding of the nature of human movement,
- other methodologies for state space reconstruction,
- the robustness of Entropy measurements with RQA, and
- variability in perception of velocity.

Considering context of human-humanoid interaction, the proposed method can be applied to

- evaluate improvement of movement performance,
- provide feedback of level of skillfulness, and
- quantify motor control problems and pathologies.

OA Publications

PEER-REVIEW CONFERENCE PAPERS

- *Towards the Analysis of Movement Variability in Human-Humanoid Imitation Activities* (HAI2017)
- *Towards the Quantification of Human-Robot Imitation Using Wearable Inertial Sensors* (HRI2017)
- *Analysis of the Movement Variability in Dance Activities using Wearable Sensors* (WeRob2016)
- *Understanding Movement Variability of Simplistic Gestures Using an Inertial Sensor* (PerDis2016)

PREPRINTS & in preparation

- *Strengths and weaknesses of Recurrence Quantification Analysis in the context of human-humanoid interaction* (ArXiv, October 2018) for Scientific Reports.
- *3D surface plots of RQA Shannon Entropy*
for Frontiers in Applied Mathematics and Statistics.

TALKS

- *Quantifying the Inherent Chaos of Human Movement Variability*
15th Experimental Chaos and Complexity Conference
- *Towards the Analysis of Movement Variability for Facial Expressions with Nonlinear Dynamics*
The 7th Consortium of European Research on Emotion Conference

FIRST Open Access PhD Thesis at UoB (since 1900)



<https://github.com/mxochicale-phd/thesis>



```

graph TD
    TS[Tissue Sample] --> H[Histology]
    H --> IHC[Immunohistochemistry]
    IHC --> FC[Flow Cytometry]
    FC --> HIST[Histogram]
    HIST --> FAS[Flow-aid Software]
    FAS --> CT[Cell Type]
    FAS --> CC[Cell Cycle]
    FAS --> SR[Summary Report]
  
```

OA PhD Thesis

- * LaTeX project
 - * Vector files

- * R version 3.4.4 (2018-03-15)
 - * R packages:
 - data.table
 - ggplot2
 - tseriesChaos
 - nonlinearTseries
 - RccArmadillo
 - * GNU Octave 4.0.2

References

- 
- Xochicale Miguel
» Nonlinear Analysis to Quantify Movement Variability in
Human-Humanoid Interaction «
Open Access Ph.D. Thesis (2019)
<https://github.com/mxochicale-phd/thesis>



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