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https://github.com/mxochicale/phd-thesis/xtras/viva

UNIVERSITY OF BIRMINGHAM | COLLEGE OF ENGINEERING AND PHYSICAL SCIENCES

Nonlinear Analyses to Quantify Movement Variability in Human-Humanoid Interaction

VIVA presentation

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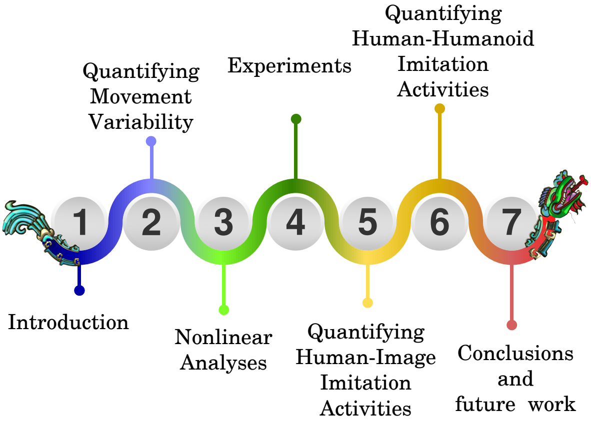
Overview


1
Introduction
2
Quantifying Movement Variability
3
Nonlinear Analyses
4
Experiments
5
Quantifying Human-Image Imitation Activities
6
Quantifying Human-Humanoid Imitation Activities
7
Conclusions and future work

MOVEMENT VARIABILITY

Why is challenging to investigate Human Movement Variably?

Human movement variability involves not only 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 (Xochicale, 2018).

Modelling Movement Variability

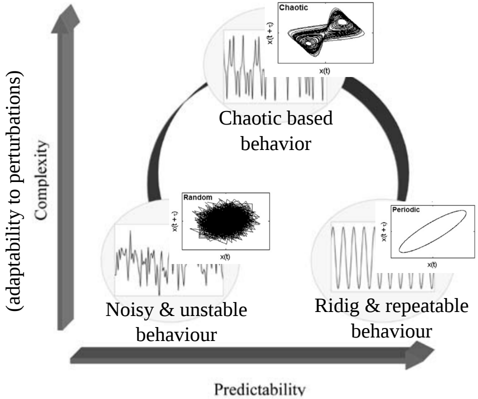


Figure 1: Theoretical Model of Optimal Movement Variability

[Stergiou et al. 2006 in **Neurologic Physical Therapy** Stergiou and Decker 2011 in **Human Movement Science**]

Nonlinear Analyses

There is no best tool to measure 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 analyses to measure MV and (ii) to understand its strengths and weaknesses.

- Approximate Entropy (Pincus 1991, 1995)
- Sample Entropy (Richman and Moorman, 2000)
- Multiscale Entropy (Costa et al., 2002)
- Detrended Fluctation Analysis (Peng et al., 1995)
- Largest Lyapunov exponent (Stergiou, 2016)
- Recurrence Quantification Analysis (Zbilut and Webber et al., 1992)

Movement Variability in Human-Humanoid Interaction

2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth)

Children's Rehabilitation with Humanoid Robots and Wearable Inertial Measurement Units

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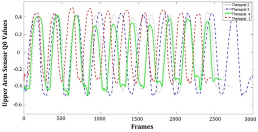
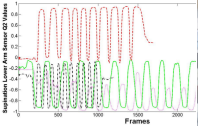
***Abstract*—The purpose of this work is to design a human computer interaction scheme for children in arm rehabilitation therapy. A humanoid robot demonstrates selected arm rehabilitation motions to children. Wearable inertial**





Research Questions

- What are the effects on nonlinear analyses (i.e. RSSs, RPs, and RQA) for different embedding parameters, different recurrence thresholds and different characteristics of time series (i.e. window length size, smoothness and structure)?
- What are the weaknesses and strengths of RQA when quantifying MV?
- How the smoothing of raw time series affects the nonlinear analyses when quantifying MV?

NONLINEAR ANALYSES

State Space Reconstruction Theorem

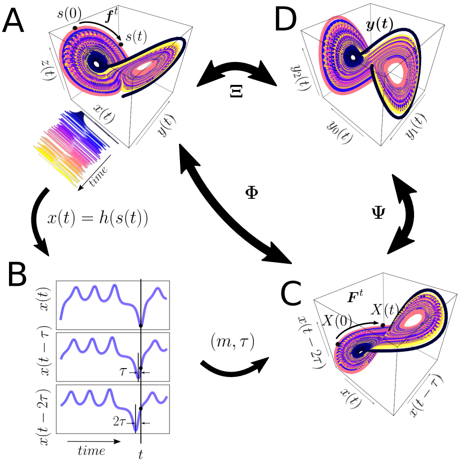


Figure is adapted from (Casdagli et al. 1991; Quintana-Duque (2012); Uzal et al. 2011)

[Takens F 1981 in **Dynamical Systems and Turbulence**; Casdagli 1991 in **Physica D**]

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 $s(t)$

[Takens F 1981 in **Dynamical Systems and Turbulence**; Casdagli 1991 in **Physica D**]

State Space Reconstruction Theorem

Uniform time-delay embedding matrix
$X(t) = \{x(t), x(t-\tau), ..., x(t-(m-1)\tau)\}$ defines a map
$\Phi : M \to \mathbb{R}^m$ 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.

[Takens F 1981 in **Dynamical Systems and Turbulence**; Casdagli 1991 in **Physica D**]

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 $\mathbf{X}_{\tau}^{m}$ are $(m, (N-(m-1)\tau))$.

[Frank et al. 2010 in **AAAI Conference on Artificial Intelligence** and Sama et al. 2013 in **Neurocomputing**]

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.

[Cao L. 1997 in **Physica D**; Kabiraj et al. 2012 in **Chaos**]

False Nearest Neighbours (FNN) for embedding dimension

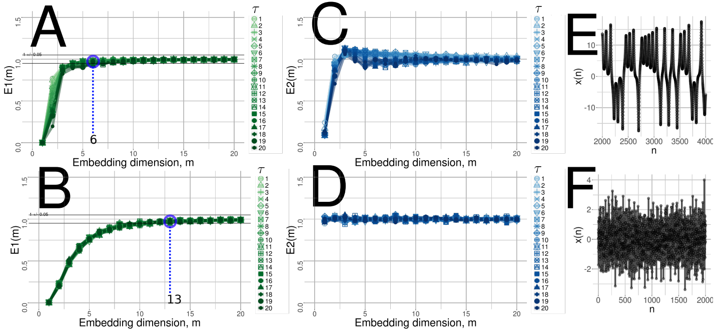


Figure is adapted from Cao L 1997 in **Physica D**

Figure 2: (A,B) $E_1(m)$ and (C, D) $E_2(m)$ values for (E) chaotic and (F) random time series

Estimation of Embedding Parameters

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 $E_2(m)$

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

[Cao L. 1997 in **Physica D**]

Average Mutual Information (AMI) for embedding delay

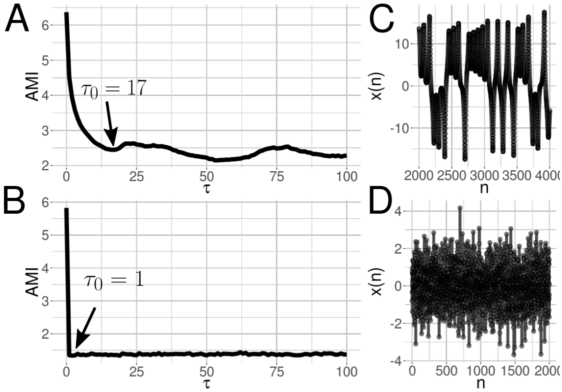


Figure is adapted from Kabiraj et al. 2012 in **Chaos**

Figure 3: (A, B) AMI values for (C) chaotic and (D) noise time series.

Estimation of Embedding Parameters

Average Mutual Information (ANN)

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

[Kabiraj et al. 2012 in **Chaos**]

Recurrence Plot

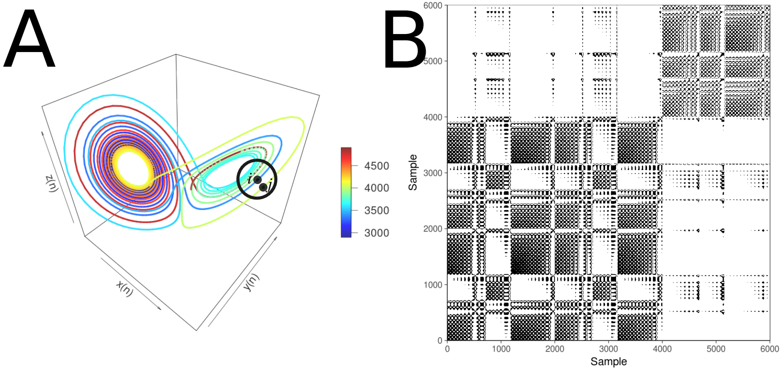


Figure is adapted from (Marwan et al. 2007)

Figure 4: (A) State space for Lorenz systems, and (B) Recurrence plot with embeddings ($m = 1$, $\tau = 1$) and $\epsilon = 5$

Recurrence Plots

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

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

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.

[Eckmann et al. 1987 in **Europhysics Letters**]

Recurrence Plot Patterns

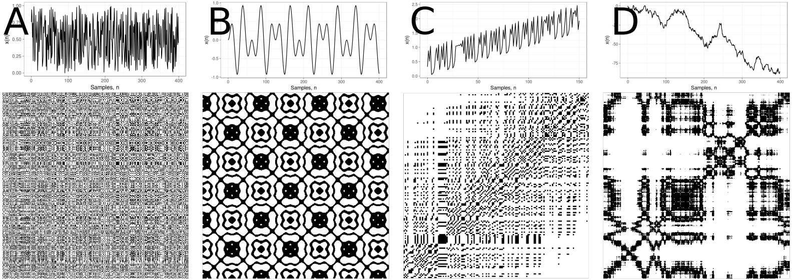


Figure is adapted from (Marwan et al. 2007)

Figure 5: Recurrence plots for (A) uniformly distributed noise, (B) super-positionet 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.)*

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

[Marwan and Webber, 2015]

Recurrence Quantification Analysis (RQA)

RATIO is the radio 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)*

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

where

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

[Marwan and Webber, 2015]

EXPERIMENT

Participants

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.

Horizontal Arm Movements

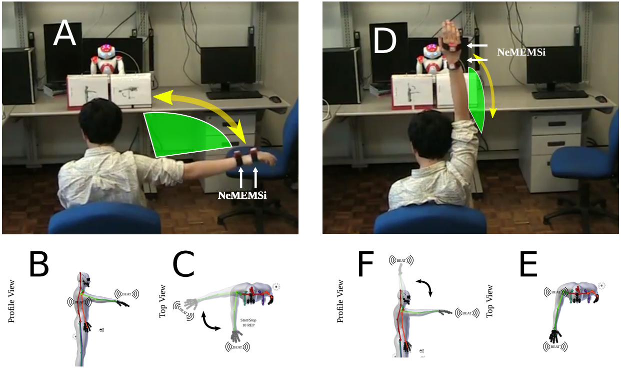


Figure 6: Arm Movements for two speed conditions: Horizontal Normal (HN) and Horizontal Faster (HF) with different window lengths.

Human-Humanoid Imitation Activities

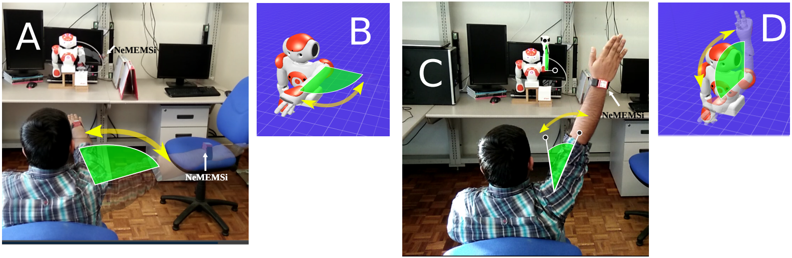


Figure 7: (A/C) Front-to-Front Human-Humanoid Imitation of Horizontal/Vertical Movements, (B/D) NAO, humanoid robot, performing Horizontal/Vertical arm movements

RESULTS

From Raw to Smoothed Time Series

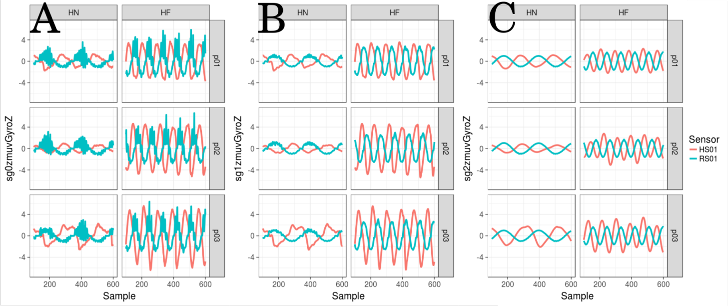


Figure 8: (A) Normalised, (B) sgolay(p=5,n=25), and (C) sgolay(p=5,n=159)

Minimum Embedding Parameters

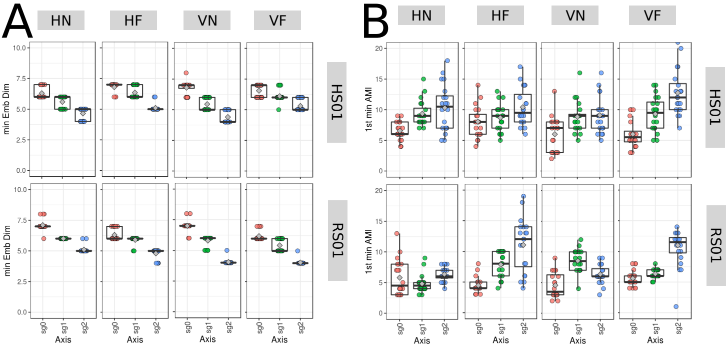


Figure 9: (A) Minimum Embedding Dimension (B) First Minimum AMI

Reconstructed State Spaces

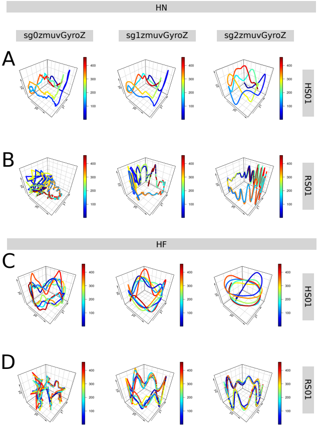


Figure 10: RSS computed with $(m = 7, \tau = 5)$

Recurrence Plots

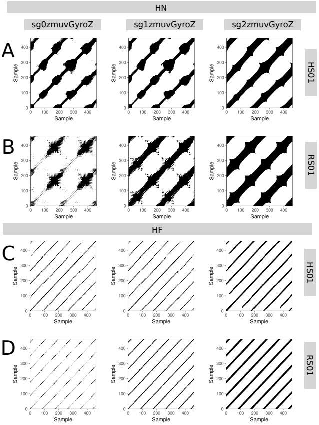


Figure 11: Recurrence Plots computed with $(m = 7, \tau = 5, \epsilon = 1)$

Recurrence Quantification Analysis

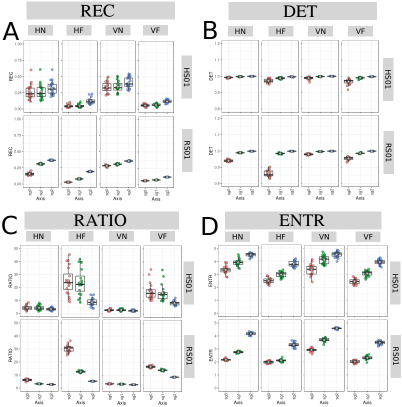


Figure 12: RQA metrics computed with $(m = 7,\ \tau = 5,\ \epsilon = 1)$

3D surfaces of RQA

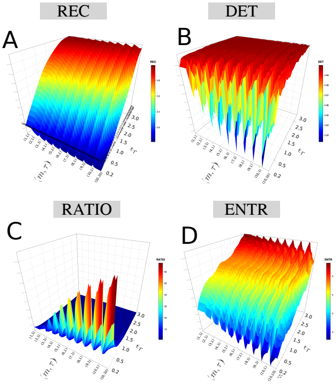
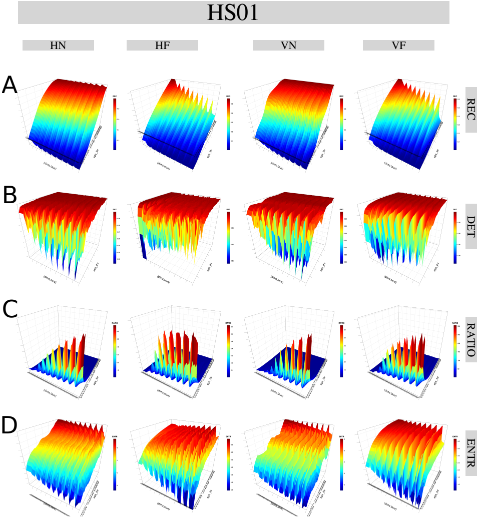
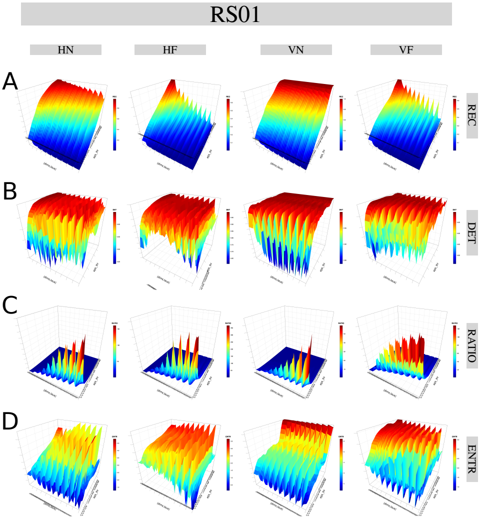


Figure 13: 3D RQA surfaces with increasing pair of embedding parameters ($0 \geq m \leq 10$, $0 \geq \tau \leq 10$) and recurrence thresholds ($0.2 \geq \epsilon \leq 3$).

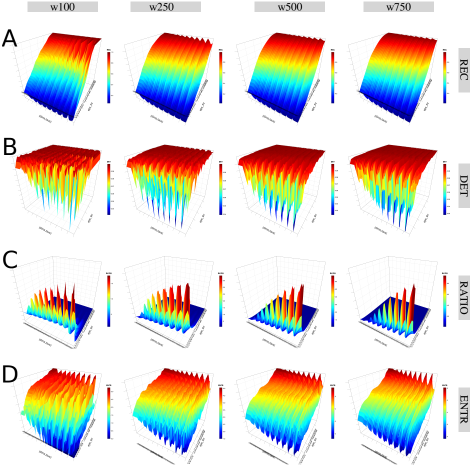
Sensors and activities



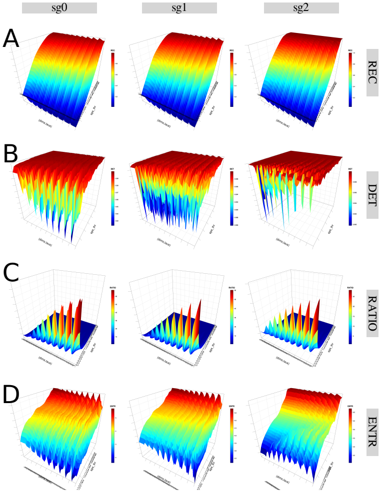
Sensors and activities



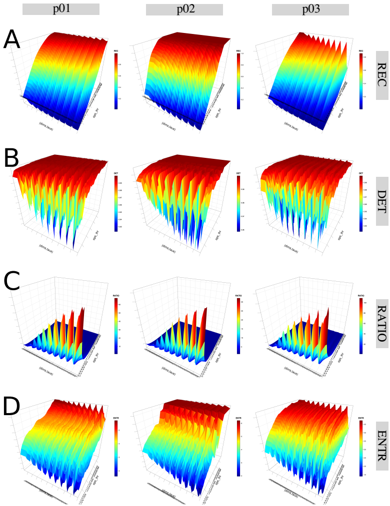
Window size lenghts



Smoothness



Participants



CONCLUSIONS

Conclusions

Modest contributions to knowledge

- Measurements of Entropy using RQA appear to be robust to real-word data (i.e. different time series structures, window length size and levels of smoothness)
- 3D surfaces of RQA are independent of either the type series or the selection of parameters.
- First open access thesis with data and code for its replication.

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.

Apply the proposed method in the context of human-humanoid interaction to:

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

References

Xochicale Miguel
»PhD Thesis as submitted«
GitHub Repositories (2018)
https:// github.com/mxochicale/phd-thesis
https:// github.com/mxochicale/phd-thesis-code-data