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Quantifying Movement Variability with Nonlinear Dynamics for Human-Humanoid Interaction

ICDEA 2019
UCL

Miguel Xochicale
https://github.com/mxochicale/

Overview

MOVEMENT VARIABILITY

Modelling Movement Variability

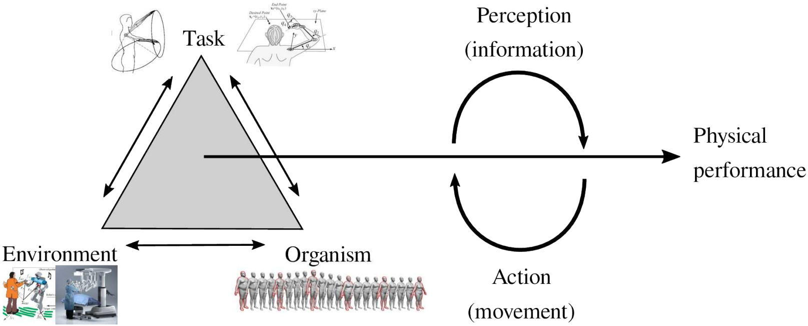


Figure 1: Newell's model of movement constrains

[Bernstein 1967 in **The co-ordination and regulation of movements**; Newell and Vaillancourt 2001 in **Hum Mov Sci**; Davids et al. 2003 in **Sport Medicine**]

Modelling Movement Variability

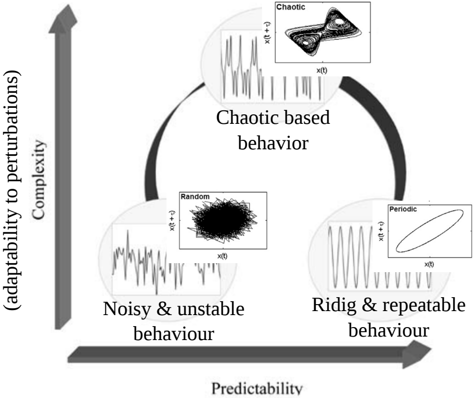


Figure 2: Theoretical Model of Optimal Movement Variability

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

NONLINEAR DYNAMICS

Methods of Nonlinear Dynamics to quantify MV

- 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)

Methods of Nonlinear Dynamics to quantify MV

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 lead me:

- **(i) to explore different methods of nonlinear dynamics to quantify Movement Variability and**
- **(ii) to understand their strengths and weaknesses with real-world data time series.**

Nonlinear Dynamics

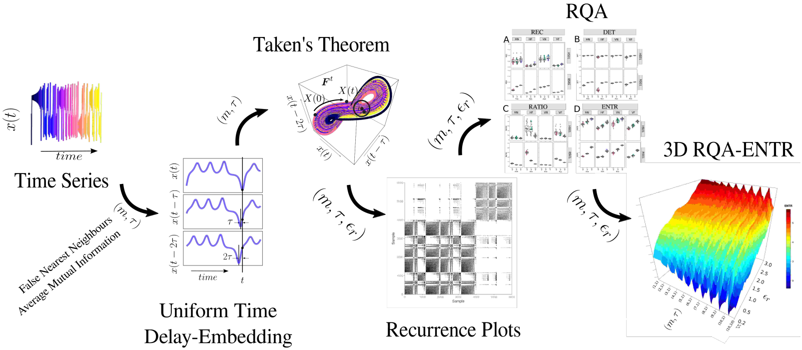


Figure is adapted from Xochicale 2019 in PhD thesis.

[Takens 1981 in **Dynamical Systems and Turbulence**; Casdagli 1991 in **Physica D**; Frank et al. 2010 in **AAAI Conference on Artificial Intelligence**; Sama et al. 2013 in **Neurocomputing**; Cao 1997 in **Physica D**; Kabiraj et al. 2012 in **Chaos**; Eckmann et al. 1987 in **Europhysics Letters**]

State Space Reconstruction Theorem (Takens's Theorem)

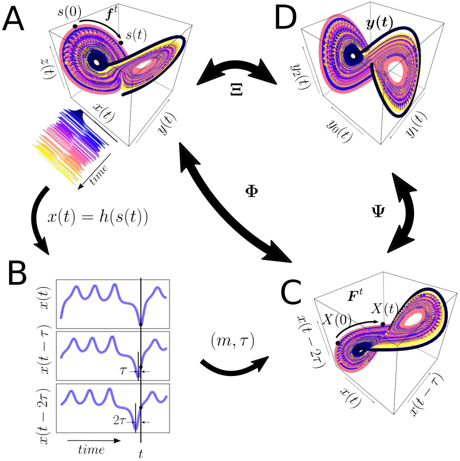


Figure is adapted from Xochicale 2019.

[Takens 1981 in **Dynamical Systems and Turbulence**; Casdagli 1991 in **Physica D**; Frank et al. 2010 in **AAAI Conference on Artificial Intelligence**; Sama et al. 2013 in **Neurocomputing**; Cao 1997 in **Physica D**; Kabiraj et al. 2012 in **Chaos**; Eckmann et al. 1987 in **Europhysics Letters**]

State Space Reconstruction Theorem (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 (Takens's 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**]

Recurrence Plot

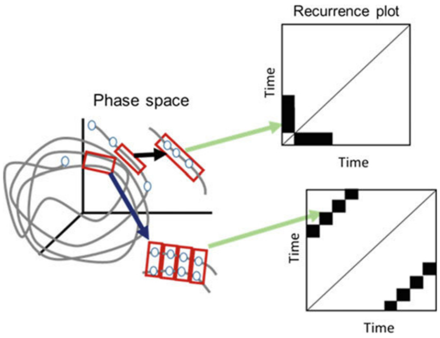


Figure is from Pawar 2018.

Figure 3: The vertical lines in the RP show that more that 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.

[Pawar et al. 2018]

Recurrence Plots

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

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

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

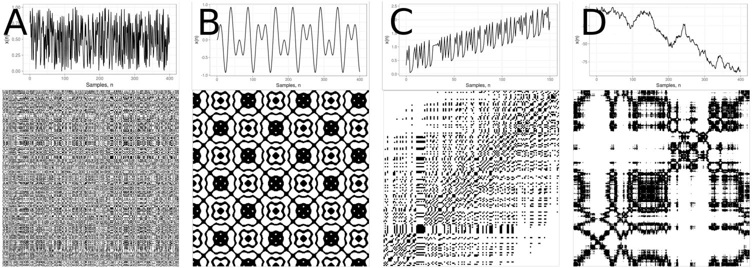


Figure is adapted from (Marwan et al. 2007)

Figure 4: 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.

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

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)*

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

where

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

[Marwan and Webber, 2015]

3D surface plots of RQA

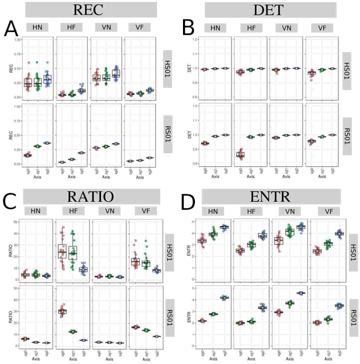


Figure is adapted from Xochicale 2019

Figure 5: Recurrence Quantification Analysis with $m_0 = 6$, $\tau_0 = 8$ and $\epsilon = 1$.

3D surface plots of RQA

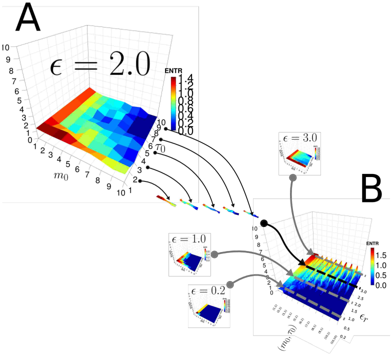


Figure is adapted from Xochicale 2019

Figure 6: (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

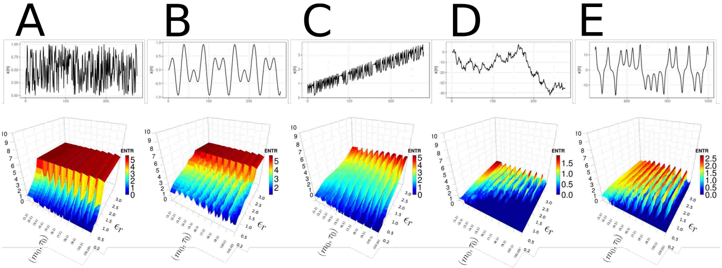


Figure is adapted from Xochicale 2019

Figure 7: 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.

EXPERIMENTS AND RESULTS

Human-Humanoid Imitation Activities

23 right-handed healthy participants were invited to imitate horizontal and vertical arm movements from an humanoid.

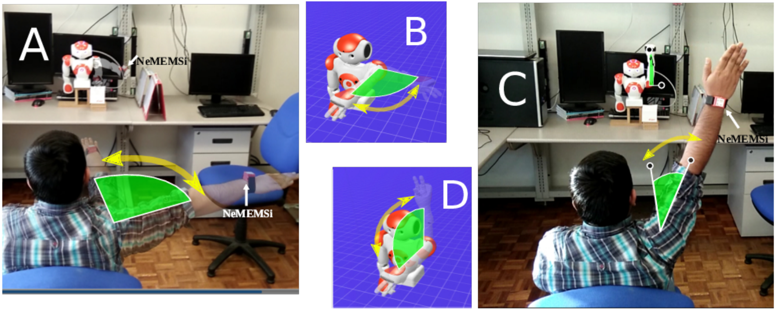


Figure 8: (A/C) Front-to-Front HHI for Horizontal/Vertical Movements. (B/D) Humanoid robot performing Horizontal/Vertical arm movements

[Xochicale 2019 in **PhD thesis**]

3D surface plots of RQA of Shannon entropy

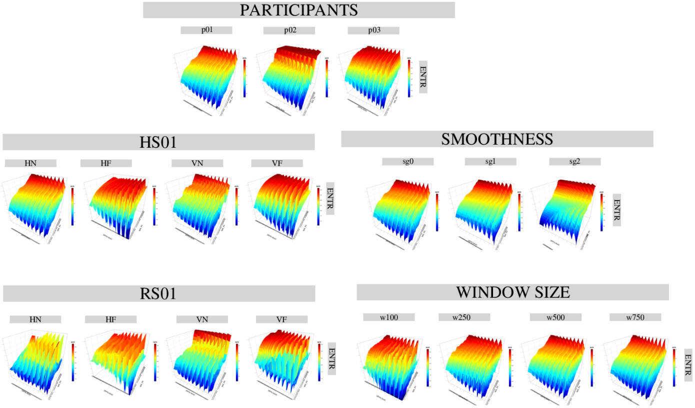


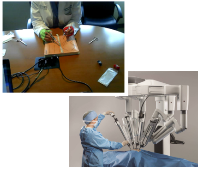
Figure is adapted from Xochicale 2019.

Figure 9: 3D surface plots for different participants, activities, sensors, smoothness and window length size.

APPLICATIONS

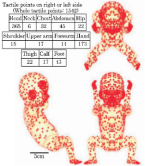
Applications of Nonlinear Dynamics

Quantification of skill learning



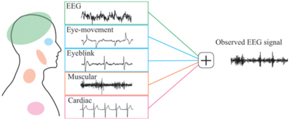
* Surgical Skills Assessment
* Robot-Assisted Surgery

Fetal behavioral development



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

Nonlinear Biomedical Signal Processing



* EEG time series
* Heart rate variability
* Eye Movements

[Zia et al., 2017 in **Computer Assisted Radiology and Surgery**; Mori 2012 in **Development and Learning and Epigenetic Robotics**; Mitsukura et al., 2017 in **Electroencephalography**; Marwan et al. 2019 in **http://recurrence-plot.tk/**]

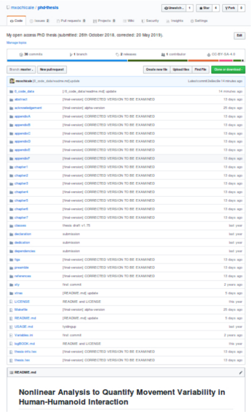
CONCLUSIONS

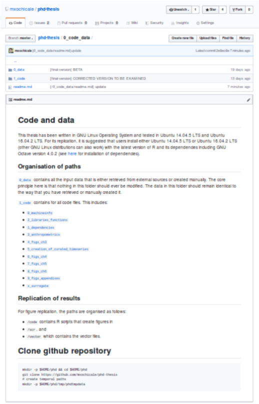
Concluding Remarks

- **What to quantify in movement variability?**
  Complexity of movement based on the degrees of freedom of a person performing a certain task in a defined environment.
- **Which methods of nonlinear analysis are appropriate to quantify movement and how methods of nonlinear analysis are affected by real-world time series data ?**
  Shannon entropy using 3D surface plots of RQA appear to be robust to real-word data (i.e. different time series structures, window length size and levels of smoothness).
- **What are these techniques good for?**
  Quantification of skill learning in HRI, dynamics of facial expressions, fetal behavioral development, or nonlinear biomedical signal processing.

FIRST Open Access PhD Thesis at UoB (since 1901)

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





OA DATA
* Multidimensional Times-series
22 participants,
4 IMUs (6 axis), and
4 Activities.

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

OA PhD Thesis
* LaTeX project
* Vector files

zenodo 201 views 122 downloads

https://doi.org/10.5281/zenodo.1473140

Submitted: 26 October 2018

Seen once: 28 February 2019

References

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