

# List of 14 corrections of my PhD thesis

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## Abstract

This PhD thesis has been submitted on 26 October 2018 and after four and half hours of scientific discussions I passed my PhD viva examination with major corrections on 11 January 2019. Hence, this document presents a list of 14 corrections of my PhD thesis in which details are given on how each of the corrections were tackled. Additionally, the clumsy use of English has been polished and third person verb tense has been used throughout all the thesis.

## 1. Tidy up use of terms – complex, non-complex, predictable, deterministic, stochastic, so they are used self-consistently.

In order to tidy up the use of these terms in Chapter 1, from point 1 to 9 the reader is being referred to Chapter two for further review of nonlinear analysis methods. Additionally, in point 10, the definition of complexity were added and related to the number of joint biomechanical degrees of freedom. In point 11, nonlinear analyses, nonlinear tools and nonlinear dynamics have been changed to nonlinear analysis in order to homogenise its use in this thesis.

### 1. (pp. 9)

ORIGINAL

”... tools when using real-world data that is commonly noisy, deterministic, stochastic or nonstationary.” to

AMENDED SENTENCE(S):

A further review of nonlinear analysis with real-world data is presented in Chapter \ref{chapter2}.

*SORTED:*

2. (pp. 10)

ORIGINAL

\* "second and third motions, which motions were more complicated" \* "they did not model well complex movements." AMENDED SENTENCE(S):

\* second and third motions, which motions were more complex  
\* completely reliable since they did not model with movements that involved more than one joint.

*SORTED:*

3. (pp. 10)

ORIGINAL

"Recently, citeguneyasu2015 presented an improvement of their previous research where less complex movements, from four physiotherapists performing five "actions, were analysed: opening a door with a key,"

AMENDED SENTENCE(S)

Then, \cite{guneyasu2015} analysed movements of more than one joint of four physiotherapists performing five actions: opening a door with a key,

*SORTED:*

4. (pp. 12)

ORIGINAL

" accordance with human aesthetics) citeppeng2015, it is important to note that one of the methodologies to create robotic dance motions is the use of chaotic dynamics which consider initial conditions to generate movements that are neither deterministic nor stochastic. "

AMENDED SENTENCE(S)

accordance with human aesthetics) \citep{peng2015},  
it is important to note that sensitivity to initial conditions  
of chaotic dynamics systems is aligned to  
the deterministic-chaotic properties of human movement  
(see Chapter \ref{chapter2} for fundamentals of  
deterministic-chaotic time series).

*SORTED:*

5. (pp. 13)

ORIGINAL

"With that in mind, I suggest that applying nonlinear analysis instead of traditional statistics in the context of human-humanoid interaction might provide a better quantification and understanding of human movements since these are generally both deterministic and stochastic."

AMENDED SENTENCE(S)

Considering the previous reviewed works in the context of human-humanoid interaction, I suggest that applying nonlinear analysis instead of traditional statistics might provide a better quantification and understanding when persons interact with humanoid robots.

*SORTED:*

6. (pp. 13)

ORIGINAL

" Similarly, little research has been done in this context with regards to the reliability of nonlinear tools when using real-world time series (e.g. window length, post-processing techniques, noise contamination, nonstationarity, chaotic deterministic, etc). "

AMENDED SENTENCE(S)

Additionally, the application of nonlinear analysis to human-humanoid interaction can contribute to the little research with regards to the reliability of nonlinear analysis with real-world data that has previously been done (see Chapter \ref{chapter2} for a review of nonlinear analysis with real-world data).

*SORTED:*

7. (pp. 19)

ORIGINAL

" are controlled by nonlinear dynamics citegoldberger1990 and data from human

movement is essentially chaotic deterministic, meaning that it is neither deterministic nor stochastic citephatze1986, preatoni2010, preatoni2013, stergiou2006. Additionally, data from the human body is noisy, deterministic, stochastic or nonstationary citepnewell1998, stergiou2011, preatoni2010, preatoni2013, caballero2014. Therefore, in this chapter fundamentals of time series, nonlinear tools and nonlinear tools with real-world data will be reviewed. ”

AMENDED SENTENCE(S)

It has been stated in Chapter \ref{chapter1} that movement variability can be modelled and quantified with methods of nonlinear analysis mainly because (i) the structures of the human physiology (e.g. lungs, neurons, etc.) suggest that many of their dynamics are controlled with nonlinear dynamics \citep{goldberger1990} and (ii) data from human movement can be chaotic-deterministic noisy, deterministic, stochastic or non-stationary \citep{hatze1986, preatoni2010, preatoni2013, stergiou2006, newell1998, stergiou2011, caballero2014}. Therefore, in this chapter fundamentals of time series, methods of nonlinear analysis to quantify movement variability and nonlinear analysis with real-world data are reviewed.

*SORTED:*

8. (pp. 19, 20)

ORIGINAL

”Biosignals from living systems can typically be non-stationary, non-linear, deterministic chaotic and noisy citepklonowski2007, caballero2014, wijnants2009, gomezgarcia2014, stergiou2006, harbourne2009, stergiou2011, hatze1986, newell1998. Therefore, it is important to provide fundamental definitions of time series which will be used through the thesis.”

AMENDED SENTENCE(S)

Biosignals from living systems can typically be noisy, deterministic, stochastic, non-linear,

non-stationary or deterministic-chaotic \citep{klonowski2007, caballero2014, wijnants2009, gomezgarcia2014, stergiou2006, harbourne2009, stergiou2011, hatze1986, newell1998}. That said, the following sections provide fundamental definitions of time series for this thesis.

*SORTED:*

9. (pp. 21)

ORIGINAL

” citepstergiou2011. Fundamentally, movement variability can be either quantified based on magnitude of the variability or the dynamics and complexity of the variability citepcaballero2014. However, finding”

AMENDED SENTENCE(S)

That said, movement variability can fundamentally be either quantified based on

(i) the magnitude of the variability or

(ii) the dynamics of the variability \citep{caballero2014}.

However, finding

the appropriate methods to quantify movement variability is still an open problem.

*SORTED:*

10. (pp. 23)

ORIGINAL

” citevaillancourt2002, vaillancourt2003 stated that there is no universal increase or decrease in complexity for MV as a function of age or disease but a dependency with the task dynamics. For example, in a constant-force task (where the task dynamics is of low dimension), older adults present less complexity due their inability to introduce additional degrees of freedom in the neuromuscular system. However, there is an increase of complexity in older adults or unhealthy adults when the task dynamic is

In contrast, inspired by citetononi1998 who modelled complexity in neural networks considering complexity versus regularity, citestergiou2006 proposed a model of complexity versus predictability variables for optimal human movement variability. The model of citestergiou2006 stated that higher complex movements are associated with rich behaviour of movements while lower complex movements are associated with poor

behaviours of movements being too rigid or too unstable. Hence, higher complexity of movements are characterised by chaotic systems, while lesser complexity of movement is characterised either as noisy systems or periodic systems (having either low amounts of predictability or high amounts of predictability) \cite{stergiou2006}.

Therefore, with the works of \cite{vaillancourt2002, vaillancourt2003} and \cite{stergiou2006}, one can quantify movement variability based on the complexity and predictability of human movement. ”

AMENDED SENTENCE(S)

Complexity for this thesis refers to the dynamics of joint biomechanical degrees of freedom of a person performing a task in a certain environment \cite{davids2003}. That said, \cite{vaillancourt2002, vaillancourt2003} stated that there is no universal increase or decrease in complexity for movement variability as a function of age or disease but a dependency with the task dynamics. For example, in a constant-force task (where the task dynamics is of low dimension), older adults present less complexity due their inability to introduce additional degrees of freedom in the neuromuscular system. However, there is an increase of complexity in older adults or unhealthy adults when the task dynamic is oscillatory because these adults have more difficulty to reduce the dimension output to a lower dimension which are the intrinsic dynamics of their resting state. In contrast, inspired by \cite{tononi1998} who modelled complexity with the variables of complexity versus regularity of neural networks, \cite{stergiou2006} proposed a model for optimal human movement variability with the variables of complexity versus predictability. The model of \cite{stergiou2006} stated that higher complex movements are associated with rich behaviour of movements, while lower complex movements are associated with poor behaviours of movements being too rigid or too unstable. Hence, higher complexity of movements are characterised by chaotic systems, while lesser complexity of movement is characterised either as noisy systems or periodic systems (having either low or high amounts of predictability) \cite{stergiou2006}.

Considering the works of \cite{vaillancourt2002, vaillancourt2003}, \cite{tononi1998} and \cite{stergiou2006}, I assume that the quantification of movement variability can be based on the complexity and predictability of human movement.

*SORTED:*

11. When appropriate, nonlinear analyses, nonlinear tools and nonlinear dynamics were changed to nonlinear analysis

Nonlinear analyses, nonlinear tools and nonlinear dynamics have been changed to nonlinear analysis in the whole thesis in order to homogenise its use.

Nicholas Stergiou [1], a stablish researcher on Human Movement Variability, use the terms of nonlinear analysis [2], nonlinear dynamics [3], and nonlinear tools [4] to quantify human movement variability. It can then be said that such ambiguity in the use of terminology is an indication that the field of these tools to quantify human movement variability are not yet fully explored.

[1] <https://scholar.google.co.uk/citations?user=CnPqqGQAAAAJ>

[2] [https://scholar.google.co.uk/citations?hl=en&view\\_op=search\\_authors&mauthors=la](https://scholar.google.co.uk/citations?hl=en&view_op=search_authors&mauthors=la)

[3] [https://scholar.google.co.uk/citations?hl=en&view\\_op=search\\_authors&mauthors=la](https://scholar.google.co.uk/citations?hl=en&view_op=search_authors&mauthors=la)

[4] no results.

*SORTED:*

Thu Apr 18 16:20:05 BST 2019

## 2. Remove abbreviations from Abstract.

1. (pp. iii)

`\begin{abstract}`

Nonlinear analysis can be applied to investigate the dynamics of time-ordered data.

Such dynamics relate to sensorimotor variability in the context of human-humanoid interaction.

Hence, this dissertation not only explores questions such as how to quantify movement variability or which methods of nonlinear analysis are appropriate

to quantify movement variability  
but also how methods of nonlinear analysis are affected  
by real-world time series data (e.g. non-stationary, data length size,  
sensor sources or noise).  
Methods are explored to determine embedding parameters,  
reconstructed state spaces, recurrence plots and  
recurrence quantification analysis.  
Additionally, this thesis presents three dimensional surface plots of  
recurrence quantification analysis with which to consider  
the variation of embedded parameters and recurrence thresholds.  
These show that three dimensional  
surface plots of Shannon entropy might be a suitable approach  
to understand the dynamics of real-world time series data.  
This thesis opens new avenues of applications in human-humanoid interaction  
where humanoid robots can be pre-programmed with nonlinear analysis algorithms  
to evaluate, for instance, the improvement of movement performances,  
to quantify and provide feedback of skill learning  
or to quantify movement adaptations and pathologies.  
\end{abstract}  
% 191 words

*SORTED:*

*Mon Mar 25 16:05:30 GMT 2019*

*Wed Apr 17 00:10:05 BST 2019 (amended)*

*Mon 6 May 10:43:55 BST 2019 (amended)*

*Mon 13 May 09:19:21 BST 2019 (amended)*

*Mon 20 May 05:32:33 BST 2019 (amended)*

### 3. Change discussion in Chapter 7 into 3er person verb tense

1. (pp. 123 to 130)  $\neg$

Where appropriate, subjects and verbs were changed from plural to singular  
(all I changed to third person)  
and clauses were amended from activite to passive.  
Also, the clumsy use of English were polished  
(i.e. spellings, typos, clumsy clauses, etc).



*SORTED:*  
*Thu Mar 28 14:18:20 GMT 2019*  
*Mon 13 May 10:52:35 BST 2019 (amended)*  
*Mon 13 May 17:16:43 BST 2019*

## 4 Add published/submitted/in preparation papers to list of page 17

1. (pp. 17)  $\neg$

Partial work of this thesis has been presented in the following four peer-reviewed conferences. Additionally, one preprint has been uploaded to ArXiv which its final version will be submitted to Scientific Reports and a manuscript for the research topic Recurrence Analysis of Complex Systems Dynamics of the journal Frontiers in Applied Mathematics and Statistics is in preparation.

*SORTED:*  
*Sun Apr 7 13:06:50 BST 2019*  
*Mon 6 May 11:15:00 BST 2019 (amended)*  
*Mon 20 May 05:41:15 BST 2019 (amended)*

**5. In Chapter 1 is important to say you assume non-stationary and non-linearity, in the methods sections you need to show that the data is non-stationary and non-linear if you are making assumptions. This could, for example, involve the use of surrogate data analysis methods.**

To tackle this correction, the following paragraphs have been added in Chapter 1 and then discussed in Chapter 7.

Additionally, code and data has been added to perform surrogate data analysis for the time-series data of the experiments in this thesis.

1. (pp. 13)

Considering the previous reviewed works in the context of human-humanoid interaction, it can then be suggested that applying nonlinear analysis methods instead of traditional statistics might provide better quantification and understanding of movement variability of persons when interacting with humanoid robots.

It is important to note that non-stationary and non-linearity of time-series data from this thesis is assumed (see Chapter \ref{chapter7} for a discussion on the reasoning, as posed by \citep{schreiber2000}, of making rather dangerous assumption).

That said, the application of nonlinear analysis methods to human-humanoid interaction activities can contribute to the not yet fully explored reliability of nonlinear analysis methods with real-world data (see Chapter \ref{chapter2} for a review of nonlinear analysis methods with real-world data).

*SORTED:*

*Tue 7 May 07:38:41 BST 2019*

*Sat May 11 17:00:57 BST 2019 (amended)*

*Mon 20 May 06:00:51 BST 2019 (amended)*

2. (pp. 133, 134)

\subsection\*{Surrogate data analysis}

Non-stationarity and non-linearity of experimental time-series data were assumed in this thesis (see Chapter \ref{chapter1}).

Such assumption was made based on the ambiguity of nonlinear analysis methods to quantify movement variability and the not yet fully explored area of application of nonlinear analysis methods in human-humanoid interaction

(see Chapters \ref{chapter1} and \ref{chapter2}).  
 From the examiners of the PhD viva,  
 one recommendation to avoid such prejudice of the type of data  
 is to test the non-linearity and non-stationarity  
 of the experimental time series data before nonlinear analysis  
 methods are applied.  
 Hence, a possible avenue to tackle such caveat  
 is to apply surrogate data analysis to test that  
 data have not been generated by "a stationary Gaussian linear  
 stochastic process that is observed through an invertible,  
 static, but possible linear stochastic function"  
 \citep[p. 2]{schreiber2000}.  
 However, applying surrogate data analysis to time series data  
 that show strong periodicity or quasi-periodicity  
 might create misleading results and perhaps provide unfair  
 conclusion  
 (see  
 \code{link{  
[https://github.com/mxochicale/phd-thesis/tree/master/  
 0\\_code\\_data/1\\_code/x\\_surrogate/00\\_timeseries/src/sinewaves](https://github.com/mxochicale/phd-thesis/tree/master/0_code_data/1_code/x_surrogate/00_timeseries/src/sinewaves)  
 }  
 on how different realisations of the same periodic sinusoidal signal  
 show to be sometimes stationarity and others non-stationarity}).  
 Hence, further research require to be done,  
 perhaps consider the works of  
 \cite{stam1998} and \cite{small2002}  
 to test weak non-stationarity  
 of periodic and quasi-periodic time series data.  
 Also, for future work,  
 it can be considered other time series data from  
 activities that involve more than one joint  
 in order to test the robustness of  
 not only nonlinear analysis methods but  
 also surrogate data analysis.

*SORTED:*

*Tue 7 May 12:30:37 BST 2019*  
*Sun 12 May 21:34:48 BST 2019 (amended)*  
*Mon 13 May 10:21:31 BST 2019 (amended)*  
*Mon 20 May 08:03:25 BST 2019 (polished)*

## 6. Say in the introduction that you want to make the work open for others to use the methods and data so that the field can advance

1. (pp. 18) To tackle this correction, I added the following subsection in Chapter 1.

```
\section{Open access PhD thesis}
This PhD thesis is open access under the licence of
Creative Commons Attribution Share Alike 4.0 International
and code and data is available at
\url{https://github.com/mxochicale/phd-thesis/} \citep{xochicale2018}.
The github repository has been created
to make this work reproducible
and perhaps help others to advance this field.
Throughout the thesis links to \R code (\,\codeicon\,)
are provided in the caption of figures in
order to reproduce their results.
See Appendix \ref{appendix:f}
for details on how code and data
is organised and how results can be replicated.
```

*SORTED:*

*Sun Apr 7 16:14:10 BST 2019*

*Sun 19 May 10:00:08 BST 2019 (amended)*

*Sun 19 May 17:24:30 BST 2019 (amended)*

## 7. Equations 3.10, 3.11 – you used mean parameters, state that you could also use maximum values and why might that be useful? In later results chapters, take care to label figures with appropriate symbols $m$ and $\tau$ or $\overline{m}_0$ and $\overline{\tau}_0$ , etc.

1. (pp. 1) To tackle this correction, the following paragraph were added in section 3.4.3 Overall minimum embedding parameters.

It is also important to mention that a maximum of individual minimum dimension embeddings,  $m_{0_i}$ , can be used instead of the overall sample mean of individual minimum dimension embeddings. The rationale for that is because the maximum value can unfold trajectories in the reconstructed state space that require a lower embedding dimension value. However such statement might be different for the maximum of individual minimum embedding delay as such maximum might not create the maximum independence between  $x(n)$  and  $x(n+\tau)$  for multiple time-series data. See Chapter \ref{chapter7} for future research on optimal embedding parameters.

*SORTED:*

*Mon Apr 22 13:54:18 BST 2019*

*Mon 6 May 11:57:17 BST 2019 (amend)*

2. (pp. )  $\wedge$  Appropriate symbols  $m$  and  $\tau$  or  $\overline{m}_0 = 6$  and  $\overline{\tau}_0 = 10$ . It is also important to mention that accidentally swithed the embedding parameters, therefore these were fixed with the appropriate values. Change parameters from  $\overline{m}_0 = 9$  and  $\overline{\tau}_0 = 6$  to  $\overline{m}_0 = 6$  and  $\overline{\tau}_0 = 10$ .

#### %CHAPTER 5

- \* Fig 5.5: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$ .
- \* Fig 5.6: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$ .
- \* Fig 5.7: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$ .
- \* Fig 5.8: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$ .
- \* 5.5 RP:  $\overline{m}_0=6$ ,  $\overline{\tau}_0=6$  and a recurrence
- \* Fig 5.9: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* Fig 5.10: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* Fig 5.11: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* Fig 5.12: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* 5.6 RQA: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* Fig 5.13: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and
- \* Fig 5.14: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=10$  and

#### %CHAPTER 6

- \* Fig 6.4: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=8$  and
- \* Fig 6.5: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=8$  and
- \* 6.5 RP: ( $\overline{m}_0=6$ ,  $\overline{\tau}_0=8$ )
- \* Fig 6.6: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=8$  and
- \* Fig 6.7: embedding parameters  $\overline{m}_0=6$ ,  $\overline{\tau}_0=8$  and

- \* 6.6 RQA: embedding parameters  $\overline{m_0}=6$ ,  $\overline{\tau_0}=8$  and
- \* Fig 6.8: embedding parameters  $\overline{m_0}=6$ ,  $\overline{\tau_0}=8$  and

*SORTED:*

*Mon Apr 22 20:45:14 BST 2019*

*Mon 6 May 12:01:39 BST 2019 (amend)*

3. (pp. x)  $\wedge$  The corrections from the thesis annotations of examiners in Chapter 3 were added.

- \* (pp.40) equation: euclidean distance symbol
- \* (pp.42) latex log
- \* (pp.48) don't need asterisks
- \* (pp.48) spellings and typos: laminarity
- \* (pp.49) spellings and typos: diagonal lines
- \* (pp.50) diagonal lines for different signals
- \* (p.50-51) spellings and typos:  $\epsilon$  is required
- \* (pp.51) spellings and typos: another exmaple of determining ..., non-statinary
- \* (pp.52) spellings and typos: exploiting effect of incrementing

*SORTED: Mon Apr 22 14:58:38 BST 2019*

## 8. Fig 5.1 and 5.2 change horizontal axis to "time" rather than "sample number" so the reader can make a more direct connection to movement, do the same in similar plots elsewhere

To tackle this correction, the following changes for figures in Chapter 5 and 6 were made.

### 1. Chapter 5

- \* Fig 4.2 changed sample by time variable
- \* Fig 5.1 and Fig 5.2 changed sample by time variable
- \* Fig 5.3 axis
- \* Fig 5.4 time axis in milliseconds
- \* Fig 5.5 to 5.8 time axis with secs
- \* Fig 5.9 to 5.12 time axis with secs
- \* Fig 5.13 and 5.14 added axis
- \* Fig 5.15 added axis
- \* Fig 5.16 to Fig 22 were amended  
(fixing ranges of parameters, axis, and captions)

*SORTED: Sat 4 May 12:49:10 BST 2019*

2. Chapter 6. Labels and time axis were fixed

- \* Fig 4.4 changed sample by time variable
- \* Fig 6.1 and Fig 6.2 amended time label
- \* Fig 6.3 Amended axis with  $m_0$ ,  $\tau$  (ms) and no axis
- \* Fig 6.4 and 6.5
- Amended time colour time axis
- \* Fig 6.6 and 6.7
- Amended time axis
- \* Fig 6.8 Amended axis
- \* Fig 6.9, 6.10, 6.11, 6.12, 6.13, and 6.14
- Amended axis and its intervals

*SORTED: Mon 6 May 09:50:44 BST 2019*

## 9. Colour code bar legends in "seconds" in Figs 5.5, 5.6, 5.7, 5.8

1. This correction were tackle with the correction number 8.

- \* Amended figures in Chapter 5

*SORTED: Sat 4 May 12:49:58 BST 2019*

2. The same has been done for Chapter 6

- \* Amended figures in Chapter 6

*SORTED: Mon 6 May 09:51:26 BST 2019*

## 10. In Chapter 4, explain how you selected which section of the time series to use, based on Fig 4.4

To tackle this correction, I reorganised section 4.6 and re-write some paragraphs. I improved the use of English language and added the following paragraph in 4.6.3 Window size of time-series

1. (pp. 62)  $\neg$

`\subsection{Window size of time-series}`

`.  
. .  
.`

Figures `\ref{fig:hii-sts}` and `\ref{fig:sts}` illustrate vertical lines to show four window lengths which were chosen in order to cover a total time of 15 seconds (750 samples) for either

(i) eight activities in human-image imitation

or (ii) four activities in human-humanoid imitation.

Figures `\ref{fig:hii-sts}` and `\ref{fig:sts}` also show the starting point of time-series data from 2 seconds (100 samples) in order to avoid picking time-series data that do not correspond to the experiment (i.e., any movements before the experiment).

The latter statement is important for the application of nonlinear analysis methods as picking dynamics of time-series data that do not correspond to the activity will therefore produce different results to the ones that only consider the duration of the activity.

*SORTED:*

*Sat Apr 20 14:32:16 BST 2019*

*Mon 6 May 13:51:36 BST 2019 (improved)*

*Mon 20 May 08:13:47 BST 2019 (polished)*

**11. In Chapter 4 clarify why these movements were chosen and the limitations of the robot (jerky movements) which might influence the data. You can use to justify the importance of smoothing, otherwise it is not clear why smoothing is so important. Then in the results chapter, point out the related features in the data**

The following paragraphs were added to tackle this correction.



1. (pp. 59)  $\neg$

\subsection{Human-humanoid imitation activities} \label{sec:experiment:hhi}  
NAO is commonly used in human-robot interaction activities because its affordability, performance and modularity. However, some of the limitations of NAO are related to  
(i) its 14 degrees of freedom (DOF) for arms and head,  
(ii) the range of joint movement and  
(iii) joint torques and velocities \citep{gouaillier2009}.  
With that in mind, four NAO's arm movements were selected, such movements are controlled by the shoulder joint for vertical and horizontal movements performed at normal and faster velocity (Figs. \ref{fig:hri} B,D). See Appendix \ref{appendix:nao} for basic information of NAO and see \cite{gouaillier2009} for detailed information of NAO's mechanical and dynamic capabilities.

*SORTED:*

*Sat Apr 20 14:12:27 BST 2019*

*Mon 6 May 16:42:46 BST 2019 (amended)*

*Mon 20 May 08:22:04 BST 2019 (polished)*

2. (pp. 63/64)  $\neg$

\subsection{Smoothing time-series}  
Applying low-pass filters is a common way to either capture low frequencies (below 15 Hz) that represent 99\% of the human body energy or to get the gravitational and body motion components of accelerations (below 0.3 Hz) \citep{anguita2013}. However, filtering such information can cut-off frequencies that are important for the conservation of  
(i) the original properties of raw time-series data and  
(ii) the structure of the time-series data in terms of width and heights. In addition to that, arm movements of NAO can sometimes produce jerky movements due to:  
(i) the control of dynamic response (fast acceleration/deceleration),  
(ii) the stiffness of the gear mechanism, or  
(iii) the high frequencies of oscillations because of resonances (see \cite{gouaillier2009} for NAO's mechanical and dynamic

capabilities).

Hence, instead of cutting out frequencies with a low-pass filter for the experiments in the context of human-robot interaction, this thesis considers the application of Savitzky-Golay filter to smooth time series data.

The latter statement might give insight into the effect of smoothness of real-world time series data for nonlinear analysis methods.

*SORTED:*

*Sat Apr 20 14:12:27 BST 2019*

*Mon 6 May 17:31:45 BST 2019 (amended)*

*Mon 20 May 08:28:09 BST 2019 (polished)*

3. (pp. 63/64)  $\neg \wedge$

**Then in the results chapter, point out the related features in the data**  
To tackle the previous point, the following paragraphs were added at: 5.3 Minimum Embedding Parameters 6.3 Minimum Embedding Parameters

%CHAPTER 5

...

appears to be near to one. In addition to that, the increase of smoothness is affected by a decrease in sample means (gray rhombus) meaning that there is a decrease of dimensionality of the dynamics of the time series data.

...

Additionally, the increase of smoothness of time series (sg0 to sg2) made the sample mean (gray rhombus) to increase which means that the maximal information to knowledge from  $x(n)$  to  $x(t+\tau_0)$  also increase.

%CHAPTER 6

Similarly to the minimum parameters in Chapter 5 (see \ref{mep-hii}), there is a decrease of minimum embedding dimension as the smoothness is increasing, meaning that there is a decrease of the dynamics of the time series data. Also, the sample mean (gray rhombus) of first minimum AMI increase as the smoothness increase,

meaning that the maximal information to knowledge at  $\tau_0$  also increase.

*SORTED:*

*Mon 6 May 18:32:55 BST 2019*

## 12. What is the significance of the black boxes in the lower left corner of some recurrence plots?

The reason for this is because time series data started from the first sample of the time series which pick up dynamics that do not correspond to the activities. Hence, the R scripts for these results were fixed to start at 100 samples (2-secs) (See wstar=100 in

```
Ca_rp_aH.R  Cb_rp_aV.R
at
/O_code_data/1_code/7_figs_ch5/05_fig5.9-5.10-5.11-5.12/code'
```

LINK:

```
https://github.com/mxochicale/phd-thesis/tree/master/
O_code_data/1_code/7_figs_ch5/05_fig5.9-5.10-5.11-5.12
```

).

This is connected with the statement given in the section subsection Window size of time-series show as follows

1. (pp. )

Figures \ref{fig:hii-sts} and \ref{fig:sts} also show the starting point of time-series data from 2 seconds (100 samples) in order to avoid picking time-series data that do not correspond to the experiment (i.e., any movements before the experiment). The latter statement is important for the application of nonlinear analysis methods as picking dynamics of time-series data that do not correspond to the activity will therefore produce different results to the ones that only consider the duration of the activity.

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### 13. In Chapter 7, discuss how the limitations on the movements (points 11) affect the general applicability of the results

The following paragraphs were added in Chapter 7 to tackle this correction.

1. (pp. 126) \_^

`\subsection*{How does the smoothing of raw time series affect methods of nonlinear analysis when quantifying movement variability?}`

`.`  
`.`  
`.`

Additionally, smoothing time-series data can preserve the structure of the dynamics of NAO's arm movements when applying nonlinear analysis, as sometimes NAO produces jerky arm movements due to

- (i) its 14 degrees of freedom (DOF) for arms and head,
- (ii) the range of joint movement,
- (iii) joint torques and velocities,
- (iv) control of dynamic response (fast acceleration/deceleration),
- (v) stiffness of gear mechanics, or
- (vi) the number of degrees of freedom

(see `\cite{gouaillier2009}` for more references on NAO's mechanical and dynamic capabilities).

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2. (pp. 127 ) \_^

`\subsection*{Smoothing time-series data}`

It has been hypothesised that one might create a closer representation of the nature of movement variability when using raw data from sensors.

However, the quality of raw time-series data from inertial sensors can be affected by changes in sample rate, drift effect of long time-series data or changes of external variables such as temperature and magnetic fields.

Additionally, humanoid robots can sometimes produce jerky movements due its mechanical and dynamic capabilities. That said, further investigation is required to be done regarding the search of the appropriate balance between and the raw data and the degree of smoothness that can get closer to the quantification of the nature of movement variability in the context of human-humanoid interaction.

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## 14. Explain how the 3D surface plots are made – you had to condense the axis labels, this does make the meaning hard to get so more explanation in the text is needed.

1. (pp. 51, 52, 53)  $\wedge$  The use of English for section "3.7.3 Some weaknesses and strengths of RP and RQA" were polished and then section "3.7.4 3D surface plots of RQA" were added to tackle this correction.

`%CHAPTER 3`

`\subsection{3D surface plots of RQA} \label{sec:3d_rqa}`

One approach to tackle some of the previously reviewed weaknesses and strengths of RP and RQA is the method of `\cite{zbilut1992}` in which 3D surface plots are created with an increase of embedding parameters ( $m$  and  $\tau$ ).

\cite{zbilut1992} explored fluctuations and gradual changes in the 3D surface plots to provide information about the selection of embeddings parameters. Similarly, considering the work of \cite{webber2018}, \cite{marwan2015} pointed out that the creation of 3D surface plots are useful for visual selection of recurrence thresholds and embedding parameters (see Fig. 1.16 in \cite{marwan2015}).

With that in mind, I propose a similar graphical approach based on the works of \cite{zbilut1992}, \cite{webber2018}, and \cite{marwan2015} in order to visualise fluctuations and changes of 3D surface plots of RQA. Hence, four variables are considered to create 3D surface plots of RQA for this thesis:

- (i) embedding dimension,
- (ii) embedding delay,
- (iii) recurrence threshold, and
- (iv) metrics of RQA.

Figure \ref{fig:fig\_37}(A) illustrates a 3D surface plot of RQA ENTR with unitary increment of embedding parameters ( $m$  and  $\tau$ ) for recurrence threshold  $\epsilon=2.0$ .

Then, Figure \ref{fig:fig\_37}(A), with other variations of recurrence thresholds (i.e.,  $\epsilon=0.2$ ,  $\epsilon=1.0$ ,  $\epsilon=3.0$ ), is used to create Fig \ref{fig:fig\_37}(B) where bands for values of  $\tau$  are concatenated to form a long band that is embedded into Fig \ref{fig:fig\_37}(B) (as illustrated by the arrows).

Additionally, five time series with their 3D surface plots of RQA ENTR are shown in Figs \ref{fig:fig\_37}(C to G) to illustrate how 3D surface plots of RQA ENTR differ from each other.

%%------(FIGURE)-----

\begin{figure}

\centering

\includegraphics[width=0.95\textwidth]{fig\_3\_07}

\caption

[3D surface plots]{

{\bf 3D surface plots.}

3D surface plots of RQA ENTR incrementing

(A) embedding dimensions ( $m$  and  $\tau$ ),

(B) embedding dimensions ( $m$  and  $\tau$ ) and recurrence threshold ( $\epsilon$ ).

Four time-series data and their 3D surface plots of RQA Entr for:

```

(C) uniformly distribute noise,
(D) super-positioned harmonic oscillation
( $\sin{\frac{1}{5}t} \sin{\frac{5}{100}t}$ ),
(E) drift logistic map ( $x_{i+1} = 4 x_i (1 - x_i)$ ) corrupted
with a linearly increase term ( $0.01 i$ ),
(F) disrupted brownian motion ( $x_{i+1} = x_i + 2\text{rnorm}(1)$ ), and
(G)  $x(t)$  solution of Lorenz system.
\R code to reproduce the figure is available at
\code{link{
https://github.com/mxochicale/phd-thesis/tree/master/0\_code\_data/1\_code/4\_figs\_ch3/
}.
}
\label{fig:fig_37}
\end{figure}
%%----- (FIGURE) -----

```

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