List of 14 corrections of my PhD thesis

Miguel Xochicale

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Abstract

This document presents a list of 14 corrections of my PhD thesis in which explanations are given on how each of the corrections were tackled. I submitted my PhD thesis on 26 October 2018 and I passed my PhD viva examination with major correction on 11 January 2019.

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 various terms in chapter 1, I refer the reader to chapter two for further review of nonlinear analysis methods. Also, complex definition were added and related to the number of joint biomechanical degrees of freedom.

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):

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* 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, citeguneysu2015 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{guneysu2015} 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 citepgoldberger1990 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 hight amounts of predictability) citepstergiou2006.

    Therefore, with the works of citevaillancourt2002, vaillancourt2003 and citestergiou2006, one can quantify movement variablity 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 \citep{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) \citep{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

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I have changed nonlinear analyses, nonlinear tools and nonlinear dynamics
to nonlinear analysis in the whole thesis as the term of nonlinear analysis
is well accepted in the community of dynamical systems.
```

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,
sampling rate changes 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}
% 194 words
```

SORTED:
Mon Mar 25 16:05:30 GMT 2019
Wed Apr 17 00:10:05 BST 2019 (adding amends)
Mon 6 May 10:43:55 BST 2019 (amends)

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

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

1. (pp. 123 to 130) _∧

```
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 use of English were improved
(i.e. spellings, typos, clumpsy 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) _∧

```
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 I am preparing a manuscript for the
research topic Recurrence Analysis of Complex Systems Dynamics
of the journal Frontiers in Applied Mathematics and Statistics.
```

SORTED:
Sun Apr 7 13:06:50 BST 2019
Mon 6 May 11:15:00 BST 2019 (amends)

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.

`https://github.com/mxochicale/phd-thesis/tree/master/0_code_data/1_code/x_surrogate`

1. (pp. 13)

```
Considering the previous reviewed works in the context
of human-humanoid interaction, I suggest that applying
nonlinear analysis 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 human-humanoid interaction
activities is assumed in this thesis
(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)

2. (pp.)

```
\subsection*{Surrogate data analysis}
Non-stationarity and non-linearity of experimental time-series data
have been assumed in this thesis
(see Chapter \ref{chapter1}).
Such assumption were made after the literature review of
nonlinear analysis methods to quantify movement variability
(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-stationary
of the experimental time series data before nonlinear analysis
methods are applied \citep{stam1998, schreiber2000}.
Hence, a possible avenue to tackle such caveat
is to apply, for instance, 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 that might contradict the literature review
of movement variability and the methods applied
to the experimental time series in this thesis.
That said, \cite{stam1998} proposed the use nonlinear
cross-prediction to test weak non-stationarity
of periodic and quasi-periodic time series data.
Therefore, it can be said that further research
requires to be done
to avoid doing any assumption to the type of data
when quantifying the phenomena of movement
variability in the context
of human-humanoid interaction.
```

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)

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 correciton, I added the following subjection in Chapter 1.

```
\section{Open Access PhD Thesis}
In 1901 the University of Birmingham published the first PhD thesis,
in July 2011 the first electronic thesis were uploaded to e-thesis
\citep{ethesis-bham},
and then, to the best of my knowledge, in 2019 my PhD thesis is the
first published open accessed PhD thesis with code and data.
Hence, a github repository has been created for this thesis
where references to open access software tools and data are
available for others to use and perhaps help
them to advance this field \citep{xochicale2018}.
```

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

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 τ 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.) _∧ Appropriate symbols m and τ 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) _∧ 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

4. (pp. x) _∧ Additionally, the use of English were improved and some I amended where appropriate the subject "we" to "I" and change active clauses to passive clauses.

SORTED: Mon Apr 22 18:49:05 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 in figures were made not only in Chapter 5 but Chapter 6.

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
Ammeded time colour time axis
* Fig 6.6 and 6.7
Ammended time axis
* Fig 6.8 Ammeded axis
* Fig 6.9, 6.10, 6.11, 6.12, 6.13, and 6.14
Ammended 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) _∧

```
\subsection{Window size of time-series}
...
Figures \ref{fig:hii-sts} and \ref{fig:sts} illustrate
vertical lines to show four window size 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
(any movements before the experiment).
The latter statement is important for the application of methods
of nonlinear analysis 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)

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) ⌃

```
\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
that control the shoulder joint for vertical and horizontal
movements performed at normal and faster velocity
were selected (Figs. \ref{fig:hri} B,D).
See Appendix \ref{appendix:nao} for basic and \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 (amend)

2. (pp. 63/64) ⌃

```
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 Appendix \ref{appendix:nao} 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 in order
to give insight into the effect of smoothness of real-world
time series data with methods of nonlinear analysis.
```

SORTED:
Sat Apr 20 14:12:27 BST 2019
Mon 6 May 17:31:45 BST 2019 (amended)

3. (pp. 63/64) _∧

   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?

This is due to the time series that were considered for the computation of recurrence plots 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 set a starting sample of 100 (2-secs) (See wstar=100 in

```
Ca_rp_aH.R  Cb_rp_aV.R
at
/0_code_data/1_code/7_figs_ch5/05_fig5.9-5.10-5.11-5.12/code‘
```

). This is connected with the statement given in the section subsectionWindow size of time-series show as follows

1. (pp. 1)

```
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
(any movements before the experiment).
The latter statement is important for the application of methods
of nonlinear analysis 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.
The latter statement is important for the application of methods
of nonlinear analysis as picking dynamics of the time-series data
that do not correspond to the activity
will therefore produce different results to the ones
that only reflect the duration of the activity.
```

SORTED: Mon 6 May 13:53:06 BST 2019

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?}

The answer to this question depends on
(i) what to quantify in movement variability and also
(ii) which hardware is involved in the collection of
time-series data.

.
.
.

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) control of dynamic response (fast acceleration/deceleration),
(ii) stiffness of gear mechanics, or
(iii) the number of degrees of freedom
(see Appendix \ref{appendix:nao} for more about
NAO's mechanical and dynamic capabilities).
```

SORTED:

2. (pp. 127) _∧

```
\subsection*{Smoothing time-series data}
I 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 can be affected
by changes in sample rate, drift effect for long time-series data or
changes of external variables such as
temperature and magnetic fields for inertial sensors.
Additionally, humanoid robots can sometimes produce
jerky movementes due ot 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 degree of smoothness
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to capture 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) _∧ 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.

```
\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 therefore 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.
Four variables are considered to create 3D surface
plots of RQA for this thesis:
(i) embedding dimension,
(ii) embedding delay,
(iii) recurrence threshold, and
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(iv) metrics of RQA.
Fig \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, Fig \ref{fig:fig_37}(A), with other variations of recurrence thresholds,
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 RQAEntr differ from each other.
%%--------------------------------(FIGURE)------------------------------------
\begin{figure}
  \centering
    \includegraphics[width=0.95\textwidth]{fig_37}
    \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 + 2rnorm(1) $), and
(G) $x(t)$ solution of Lorenz system.
R code to reproduce the figure is available in \cite{xochicale2018}.
}
    \label{fig:fig_37}
\end{figure}
%%--------------------------------(FIGURE)------------------------------------
```

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