Chapter 7

Conclusions, contributions and future work

7.1 Conclusions

Considering the methods for nonlinear analyses to measure movement variability and the experiments for human-image interaction and human-humanoid intereaction, we can conclude that nonlinear analyses with real-world data is possible. However, in the following sections, we will point out positives and negatives of this thesis by answering the research questions.

7.1.1 What are the effects of different parameters for nonlinear analyses with different characteristics of time series?

Generally, it is evidently that time series from different sources of time series (participants, movements, axis type, window size lengths or levels of smoothness) will present differences for not only the computation time of the embedding parameters but also for the patterns in RRSs, RP, RQAs and 3D surfaces of RQA metrics.

7.1.2 What are the weaknesses and strengths of RQA metrics when quantifying MV?

It can be noted that not only the activity type, window size length and structure of the time series affects the values of RQA metrics but also certain RQA metrics are better to describe the dynamics of a determined type of movement.

RQA metrics with fixed parameters

We found the following when RQA metrics were computed with fixed embedding parameters ($m = 6$ and $\tau = 8$) and recurrence thresholds ($\epsilon = 1$). REC values, representing the % of black points in the RPs, were more affected with an increase for normal arm movements (HN and VN) than for faster velocity arm movements (HF and VF) with the sensor attached to the participants (HS01). Such decrease of REC values from normal to faster velocity arm movements is also presented in the time series from the sensor attached to the robot (RS01), and REC values for RS01 appear to be more constant than those from HS01.

DET values, representing predictability and organisation in the RPs, present little variation in the any of the time series and little can be said but the effect of the increase of smoothness of time series which made DET values appear to be more similar and constant. In contrast, RATIO values, which represent dynamic transitions, were more variable for arm movements performed at faster velocity (HF and VF) than normal velocity (HN and VN) with the sensor attached to the participants (HS01). For time series from the sensor attached to the robot (RS01), RATIO values for horizontal arm movements (HN, HF) appear to vary more than values coming from vertical arm movements (VN, VF). With that in mind, it can be said that RATIO values can represent better movement variability than the use of REC or DET metrics, particularly their dynamics transitions of imitation activities in each of the conditions for time series.

In the same way as the previous metrics, ENTR values for HN arm movements were higher than values for HF arm movements and ENTR values varied more for sensor attached to participants (HS01) than ENTR values for sensors of the robot (RS01). It is evidently that the higher the ENTR metric is, the more complex the dynamics of the movements are, however, ENTR values for HN appear a bit higher than HF values. With that in mind, we hypothesise this happens because of the structure the time series appear more complex for HN than HF arm movements (presenting less stability at normal velocity).

We also explored the effect of smoothness of raw-normalised time series for RQA metrics where, for instance, REC and DET values appear to be constant. Hence, REC and DET values were little affected by the smoothness of time series. However, the effect of smoothness can be well noticed for both RATIO and ENTR values where a slightly but notable decrease in the amplitude of the values in any of the time series conditions is presented.

RQA metrics with different parameters

Patterns in RPs and metrics for RQA are independent of embedding dimension parameters (Iwanski and Bradley, 1998), however, that is not the case when using different recurrence thresholds. Hence, 3D surfaces of RQA with increments of embedding parameters and recurrence thresholds were computed to show their variations with respect to different characteristic of the time series such as window size length, participants, sensors and levels of smoothness. In general, it can be noted that the patterns in 3D surfaces of RQA are sensible to the increase of embedding parameters and recurrence threshold, meaning that stability of RQA metrics is dependant on changes of embedding parameters and recurrence thresholds.

7.1.3 How the smoothing of raw time series affects the non-linear analyses when quantifying MV?

The answer depends on what one needs to measure, for instance, to avoid erratic changes in the metrics, smoothing the raw signals helps to have a more defined and constant metric for different sources of time series. In contrast, when using raw data, the metrics might create a closer representation of the nature of movement variability.

Nonlinear tools are generally affected by the smoothness, showing mainly proportional smoothness in the metrics. Also some RQA metrics (e.g. DET and ENTR) are more robust to the effect of smoothness of time series.

Additionally, it was also found that using different levels of smoothness for time series helps to visualise the variations of movements between participants (e.g. RSSs, RPs and RQA). It is important to mention that some RQA's metrics (e.g. DET and ENTR) are more robust to the effect of smoothness of time series. However, we believe that further investigation is required to find the right balance between the level of smoothness of the signal and its representations with RSS, RP and RQA.

7.2 Contributions

The contribution to knowledge in this thesis is with regards to experimental work that test the weaknesses and strengths of nonlinear dynamics tools with real-world data in the context of human-humanoid interaction, specially with the use of RQA metrics. Hence, thorough the visualization of 3D surface patterns of RQA metrics, it was found that RQA metrics are not only dependent on dimension parameters but dependent on recurrence thresholds, which is an extension of the work of Iwanski and Bradley (1998) who pointed out that RQA metrics are independent of dimension parameters. In this thesis, it was also found that the patterns of 3D surfaces of ENTR values can be used to model any of the effects of movement variability of the activities as well as the post processing of time series.

7.3 Future work

7.3.1 Inertial sensors

To have fundamental understating of the nature of signals collected through inertial sensor in the context of human-robot interaction, future experiments can be conducted considering the application of derivates to the acceleration data. With that in mind, it can then explore (i) the jerkiness of movements and therefore the nature of arm movements which typically have minimum jerk (Flash and Hogan, 1985), (ii) the relationship with different body parts, for instance, how rapid or slowly one perform arm and legs movements as we grow up (de Vries et al., 1982; Mori and Kuniyoshi, 2012) or (iii) the application to time series of higher derivatives of displacement with respect time such as jounce, snap, crackle and pop (Eager et al., 2016).

7.3.2 Nonlinear analyses

While working with different nonlinear analyses we bumped into interesting areas that will be part of our future lines of research.

Embedding parameters

When using the False Nearest Neighbour method of Cao (1997), where the values for $E_1(m)$ stop changing to find the minimum embedding dimension, a threshold should be defined in order to obtain the minimum embedding dimension m_0. Hence, a further investigation is required for the selection of the threshold in the $E_1(m)$, as the selection of the threshold in this thesis is only based on no particular method but visual inspection of the $E_1(m)$ curves.

Similarly, further research is required to be done with regards to the selection of the minimum delay embedding because it is not clear: (i) why the choose of the first minimum of the AMI is the minimum delay embedding parameter (Kantz and Schreiber, 2003) or (ii) why the probability distribution of the AMI function is computed with the use of histograms which depends on a heuristic choice of number of bins for the AMI partitioning (Garcia and Almeida, 2005). Additionally, "the AMI method is proposed for two dimensional reconstructions and extended to be used in a multidimensional case which is not necessarily hold in higher dimensions" (Gómez-García et al., 2014, p. 156).

Other methodologies for state space reconstruction.

In addition to the Uniform Time-Delay Embedding method to reconstruct state spaces other methods have been investigated stating a better dynamic representations of time series in the reconstructed state spaces such as: (i) the nonuniform time-delay embedding methodology where the consecutive delayed copies of $\{\boldsymbol{x}_n\}$ are not equidistant. Such method has been proved to create better representations of the dynamics of the state space to analyse quasiperiodic and multiple time-scale time series, and (Pecora et al., 2007; Quintana-Duque and Saupe, 2013; Quintana-Duque, 2012, 2016; Uzal et al., 2011), and (ii) uniform 2 time-delay embedding method which takes advantage of finding an embedding window instead of the traditional method of finding the embedding parameters separately (Gómez-García et al., 2014).

RQA parameters

Having presented our results with RQA metrics, we believe that further investigation is required to have a better understanding of the RQA metrics and ensure its robustness in many of its applications. For example, Marwan et al. (2007) and Marwan and Webber (2015) reviewed different aspects to compute RPs using different criteria for neighbours, different norms (L_{1-norm}, L_{2-norm}, or $L_{\infty-norm}$) or different methods to select the recurrence thresholds such as using only certain percentage of the signal ($\sqrt{m_0}\times$ 10% of the fluctuations of the time series) (Letellier, 2006), select a determined amount of noise or using a factor based on the standard deviation of the observational noise Marwan et al. (2007).

Advanced RQA quantifications

In addition to the applied RQA metrics (REC, RATIO, DET and ENTR) for recurrence quantification, we believe that other line of future research for this thesis is the investigation of further quantification methodologies of the RP based on complex networks statics, calculation of dynamic invariants, study of the intermittency in the systems, applying different windowing techniques or the study of bivariate recurrence analysis for correlations, couplings, coupling directions or synchronisation between dynamical systems (Marwan et al., 2007; Marwan and Webber, 2015).

7.3.3 Variability in perception of velocity

While conducting the experiments with different arm movements velocities (e.g. normal and faster), we realised that participants perceive velocity differently, shedding light for a have better understanding on why each participant perceive body movement velocity differently and how to quantify such variability of perception of movement. For instance, some participants considered a normal velocity movement as a slow velocity movement and some others considered a slow velocity movement as being performed in normal velocity. With that in mind, we hypothesise that the differences in perception of velocities are related to the background of each person, for example, persons who have received musical training in their infancy are more aware of their body movements. It would also be interesting to ask participants to move in three different velocities without any constrain in order to capture the natural movements of slow, normal and faster velocity arm movements.

7.3.4 A richer dataset of time series

It should also be highlighted that the experiments for this thesis are limited to twenty three healthy right-handed participants of a range age of mean 19.8 and SD=1.39, for which participants of different ages, state of health and anthropomorphic features would create a richer dataset of time series.