Chapter 7

Conclusions, contributions and future work

7.1 Conclusions

The main conclusion for this thesis is that quantification of MV in the context of human-humanoid interaction using nonlinear analyses with real-world data is possible. However, we will point out some positives and negatives of this thesis by answering the research questions.

7.1.1 What are the effects of different parameters for Nonlinear Tools with different characteristics of time series?

In general, it is evident~~ly~~ that time series from different sources (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. Are there consistent variations, do some differences matter more than others?

7.1.2 How sensitive or robust are RQA metrics when quantifying MV?

In general, 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 (predicability, organisation of the RPs, dynamics transitions, or complexity and determinism) But by how much?

RQA metrics with fixed parameters

Considering that RQA metrics were computed with fixed embedding parameters ($m = 6$ and $\tau = 8$) and recurrence thresholds ($\epsilon = 1$), we found the following. REC values, representing the % of black points in the RPs, were more affected with an increase in (of what?) normal movements (HN and VN) than faster velocity movements (HF and VF) for the sensor attached to the participants (HS01). Such decrease of REC values from normal to faster velocity 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. Similarly, DET values, representing predictability and organisation in the RPs, present little variation in ~~the~~ any of the time series where little can be said but the effect of smoothing the time series made DET values appear to be more similar and therefore 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) for the sensor attached to the participants (HS01). For time series coming from sensor attached to the robot (RS01), RATIO values from horizontal movements (HN, HF) appear to vary more than values coming from vertical movements (VN, VF). With that in mind, it can be said that RATIO values can be represented better than using REC or DET metrics for the variability, particularly their dynamics transitions of imitation activities in each of the

as RATIO is a composite what causes this?

conditions for time series. In the same way, ENTR values for HN were higher than values for HF 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 entropy the more complex the dynamics are, however, ENTR values for HN appear a bit higher than HF values, we believe this happens because of the structure the time series which appear more complex for HN than HF movements (presenting a more consistence repetition). Explain

We also explored the effect of smoothness of raw-normalised data for RQA metrics where, for instance, REC and DET values appear to be constant and therefore, they 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 decrease of 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 Is it fine to smooth raw time series for the quantification of MV?

rewrite question

The answer depends on what ones needs to measure, for instance, to avoid erratic changes in the metrics, smoothing the raw signals helps to have a more defined metric. In contrast, when using raw data, the metrics might create a closer representation of the variability.

With regard to the nonlinear tools, these are generally affected by the smoothness, showing also a proportional smoothness in the metrics. Also some RQA's metrics (e.g. DET and ENTR) are more robust to the effect of smoothness of time series.

It was also found that using a different levels of smoothness for time series helps to visualise the variations of movements between participants using RSSs, RPs and RQA. Also, 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 using RSS, RP and RQA. Particularly, where the level of smoothness does not affect the variation of each of the movements' quantification.

7.2 Contributions

This thesis contributes ~~with~~ to experimental work to test the weakness and strengths of nonlinear dynamics tools with real-world data in the context of human-humanoid interaction, specially with the use of RQA metrics. Iwanski and Bradley (1998) pointed out that RQA metrics are independent of dimension parameters but through the 3D visualization of RQA patters in this thesis we found that RQA are not only dependent on dimension parameters but dependent on recurrence thresholds. What else?

7.3 Future work

7.3.1 Inertial sensors

To have more fundamental understating of nature of signals collected through inertial sensors in the context of human-robot interaction, future experiments can be conducted considering the application of derivates to the acceleration data. It can then explore the jerkiness of movements and therefore the nature of arm movements which typically have minimum jerk (Flash and Hogan, 1985), its relationship with different body parts, for instance, how rapid or slowly we perform arm and legs movements as we grow up (de Vries et al., 1982; Mori and Kuniyoshi, 2012) or the application 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

Considering the False Nearest Neighbour method (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 why the choose of the first minimum of the AMI is the minimum delay embedding parameter (Kantz and Schreiber, 2003) or 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 then 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 to perform such reconstruction 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 (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). In general, uniform 2 time-delay embedding method computes m with False Nearest Neighbour (FNN) algorithm and τ is computed as $\tau = d_w/(m-1)$, where d_w is given by the minimisation of the Minimum Description Length (Small and Tse, 2004).

Both methods (i) the nonuniform time-delay embedding or (ii) the uniform 2 time-delay embedding will create another line of our future research in order to have nonlinear tools that describe better the dynamics of the time series in the reconstructed state spaces.

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. 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 threshold ϵ. With regard to the selection of the recurrence threshold, one can determined it by 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 in different ways. For instance, some participants considered a normal velocity movement as 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 receive musical training in their infancy are more aware of their body movement. 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. That sheds light of the need of another lines of research in our future work in order to have better understanding on why each participant perceive body movement velocity differently and how to quantify such variability of perception of movement.

7.3.4 A more rich 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 SD=1.39, for which participants of different ages, state of health and anthropomorphic features would create more richness in the dataset of time series.

Applications for the approach?