Chapter 8

Conclusion

What were the research questions? How were these answered? How does you work extend and advance the field?

8.1 Discussion

~~It is evidently that~~ Time series from different sources (participants, movements, axis type, window length or levels of smoothness) presents visual differences for embedding parameters and therefore for RRSs. For which, the selection of embedding parameters was our first challenge where we computed embedding parameters for each time series and then computed a sample mean over all time series in order to get two embedding parameters to compute all RSSs with its corresponded type of movement. Then we found that the quantification of variability with regard to the shape of the trajectories in RSSs requires more investigation since our original proposed method base on euclidean metric failed to quantify those trajectories. Specially, for trajectories which were not well unfolded. With that in mind, we proceed to take advantage of four RQA metrics (REC, DET, RATIO and ENTR) in order to avoid any subjective interpretations or personal bias with regard to the evolution of the trajectories in RSSs.

8.1.1 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, which represents the % of black points in the RPs, were more affected with and increase in normal speed movements (HN and VN) than faster movements (HF and VF) for the sensor attached to the participants (HS01). Such decrease of REC values from normal speed to faster speed movements is also presented in data from sensor attached to the robot (RS01), and little can be said with regard to the dynamics of the time series coming from RS01. 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. In contrast, RATIO values, which represent dynamic transitions, were more variable for faster movements (HF and VF) than normal speed movements (HN and VN) with sensors attached to the participants (HS01). For data coming from sensors attached to the robot (RS01), RATIO values from horizontal movements (HN, HF) appear to vary more than values coming from vertical movmentes (VN, VF). With that, it can be said that RATIO values can represent a bit better than REC or DET metrics for the variability of imitation activities in each of the 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 than ENTR values for sensors of the robot. 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, for which we believe this happens because of the structure the time series which appear more complex for HN than HF movements which presented a more consistence repetition.

We observed that some RQA metrics are affected by the smoothness of data. For which, we also explored the effect of smoothness of raw-normalised data where, for example, REC and DET values were not affected by the smoothness of data since these

In general, activity type, window length and structure of the time series affects the values of the metrics of RQA for which certain RQA metrics are better to describe determined type of movement. Using determined RQA metrics depends on what one want to quantify, for instance, one can find predicability, organisation of the RPs, dynamics transitions, or complexity and determinism.

Similarly, such differences in time series created differences in each of the RQA metrics, for instance, RATIO and ENTR are helpful to distinguish differences in any of the categories of the time series (sensor, activity, level of smoothness and number of participant), however for certain time series (data from the sensor attached to the robot) seemed to have little variations between each of the participants. The latter phenomena was in a way evidently as robot degrees of freedom did not allow it to move with a wide range of variability.

8.3 Future Work

8.3.1 Inertial Sensors

To have more fundamental understating of nature of signals collected through inertial sensors in the context of human-robot interaction, we are considering to apply derivates to the acceleration data. We 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 de Vries et al. (1982); Mori and Kuniyoshi (2012) or the application of higher derivatives of displacement with respect time such as snap, crackle and pop Eager et al. (2016).

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8.3.2 RQA

Having presented our results with RQA metrics, we believe that further investigation is required to have more robust metrics. For example, Marwan et al. Marwan et al. (2007); 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, such as using certain percentage of the signal Letellier (2006), the amount of noise or using a factor based on the standard deviation of the observational noise among many others Marwan et al. (2007).

In this work, an experiment is performed in the context of human-humanoid imitation activity to test nonlinear dynamics methods to quantify human movement variability. The presented results that illustrate the potential of nonlinear dynamics tools by providing a balanced review of positive and negatives aspects of each technique to quantitatively and qualitatively measure movement variability.

With regards to the visual inspection and understanding of the patters for reconstructed state spaces and recurrence plots, it can also be concluded that the performance of such tools is subjective since biased personal data interpretation might be provided. Hence, without any bias, RQA metrics (REC, DET, RATIO and ENTR) help us to show such differences of movement variability for difference categories of the time series (participants, movements, axis type, window length or levels of smoothness). Furthermore, it was noticed that each of the metrics of RQA show the differences but particularly the metrics of RATIO and ENTR are helpful to distinguish the differences in each of the categories of the time series.

Although RPs and metrics for RQA are independent of embedding dimension Iwanski and Bradley (1998), it was found that recurrence threshold values can modify the results for both RPs and RQA. This work has carried out experiments on different activities in which the sensor's axis was representative of difference of structures in the time series. Hence, further investigation is required. In a similar experiment carried out by Letellier (2006), an equation was defined following several trials for the selection of recurrence threshold. This equation was used to determine the recurrence plot ($\sqrt{m_0}\times$ 10% of the fluctuations of the 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.

It is important to mention that while performing the experiments with different arm movements speeds (e.g. normal and faster), it was realised that participants perceive speed in different ways. For instance, some participants considered a normal speed movement as slow speed movement and some others considered a slow speed movement as being performed in normal speed. That sheds light of the need for future work to understand how each participant perceive body movement speed differently. It should also be highlighted that the experiment is limited to twenty healthy right-handed participants of an age range 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.

Additionally, a more meaningful understating of the nature of the signals collected with inertial sensors is required in cases where by derivate the acceleration data, jerk movements and its relationship with different body parts can be explored de Vries et al. (1982); Mori and Kuniyoshi (2012) and its nature of arm movements considered to have typically minimum jerk Flash and Hogan (1985).