Chapter 1

Introduction

1.1 Background

Human movement involves not only multiple joints and limbs for a specific task in a determined environment but also external information processed through all of our available senses and our prior experiences. Recent studies in human motion recognition have revealed the possibility of estimating features from lower dimension signals to distinguish differences between styles of movement, such as pedalling (Quintana-Duque, 2012, 2016) or walking (Frank et al., 2010; Samà et al., 2013). Similar approaches have been applied to pattern recognition of physiological signals (speech and heart pathologies or epilepsy) (Gómez-García et al., 2014).

Signals of lower dimension are generally time series of one-dimension in $\mathbb{R}$ which commonly have high nonlinearity, complexity, and non-stationarity (Caballero et al., 2014; Gómez-García et al., 2014; Huffaker et al., 2017). With that in mind, traditional methods in time-domain or frequency-domain generally tend to fail when detecting tiny modulations in frequency or phase (Marwan, 2011). This can mean that subtle signatures of each individual's movement could be missed using traditional methods. However, methods of nonlinear time series analysis can quantify such subtleties in human movement variability (Frank et al., 2010; Gómez-García et al., 2014; Marwan, 2011; Packard et al., 1980; Quintana-Duque, 2012, 2016; Samà et al., 2013; Stergiou and Decker, 2011). Recently, Bradley and Kantz (2015) reviewed methods for nonlinear time series analysis, such as the reconstructed state space (RSS) (Takens, 1981), recurrence plots (RP) (Eckmann et al., 1987) and recurrence quantification analysis (RQA) (Zbilut and Webber, 1992). Such methods are implemented using embedding parameters (m and τ). However, the computation of embedding parameters is still an open problem since there is no general technique to compute the embedding parameters because time series are system-dependent, meaning that defined parameters may only work for one purpose, e.g., prediction, or may not work well for other purposes e.g., computing dynamical invariants (Bradley and Kantz, 2015).

Additionally, the quality of the time series signals is reflected on the reliability of methods of nonlinear analysis. For instance, methods to compute embedding parameters e.g., autocorrelation, mutual information, and nearest neighbour, require data which are well sampled and with little noise (Garland et al., 2016) or need to be purely deterministic signals (Kantz and Schreiber, 2003). Similarly, methods such as RSS, RP and RQA can break down when datasets have different length, different accuracy and precision (Frank et al., 2010), or when data are contaminated with different sources of noise (Garland et al., 2016). It is surprising that despite these problems, methods of nonlinear analysis have proven to be helpful to understand and to characterise time series in the context of human movement (Bradley and Kantz, 2015; Frank et al., 2010; Gómez-García et al., 2014; Marwan, 2011; Quintana-Duque, 2012, 2016; Samà et al., 2013; Stergiou and Decker, 2011). Another point to consider when analysing time series with methods of nonlinear analysis is the appropriate use of post-processing techniques such as interpolation, normalisation or filtering. However, to my knowledge, there is little research on the effects and interpretation of post-processing techniques with methods of nonlinear analysis such as RSSs, RPs and RQA.

1.2 Movement variability

Variability is inherent within and between all biological systems (Newell and Corcos, 1993). For instance, variability has been studied in electroencephalographic signals in human brains (Klonowski, 2007), in physiological signals like the heart rate variability (Rajendra Acharya et al., 2006; Schumacher, 2004), respiratory patterns of rats (Dhingra et al., 2011), in speech variability where not only the linguistic aspect is investigated but factors like gender, age, social, state of health, emotional state are strongly related to uniqueness of the speaker (Benzeghiba et al., 2007) or even in odor responses based on cultural background and gender (Ferdenzi et al., 2013).

Variability has also been well studied in human body movement, where, for instance, Bernstein (1967) stated that no human movement is repeated exactly with the same trajectory. With that in mind, movement variability has been used as a model of fatigue to prevent chronic musculoskeletal disorders (Mathiassen, 2006; Srinivasan and Mathiassen, 2012). Movement variability has also been considered as an indicator of skilled performance in sport science where, for instance, Wagner et al. (2012) show how movement variability based on statistical analysis varies with skill for three levels of throwing techniques (low-skilled, skilled, and high-skilled). Therefore, Bartlett et al. (2007) concluded that movement variability is ubiquitous across sports (javelin throwing, basketball shooting or running). Another interesting example is that movement variability can be considered as an identifier for personal trait (Sandlund et al., 2017), where many factors of the human body can be considered for identification, such as: age (Krüger et al., 2013; MacDonald et al., 2006; Stergiou et al., 2016; Vaillancourt and Newell, 2003), gender (Svendsen and Madeleine, 2010), pain status (Madeleine et al., 2008; Sandlund et al., 2008), body composition (Chiari et al., 2002), work experience (Madeleine and Madsen, 2009), pace, movement direction or cognitive demands like perception, memory or capacity for introspection (Kanai and Rees, 2011; Srinivasan and Mathiassen, 2012). Additionally, Bartlett et al. (2007) highlighted that movement variability can be interpreted from different theoretical disciplines. For instance, a cognitive control theorist considers variability as undesirable noise and variability is reduced as skill increases, meaning that "becoming dexterous freezes unwanted degrees of freedom in the kinematic chain" (Bartlett et al., 2007, p. 238). In contrast, an ecological motor control specialist considers movement variability either as a functional role in human movement for "coordination change and flexibility to adapt" in different environments (Bartlett et al., 2007, p. 238) or as an exploration and exploitation of body parts in the "perceptual-motor workspace" (Herzfeld and Shadmehr, 2014; Wu et al., 2014).

Stergiou and Decker (2011), in contrast, highlighted that an optimal state of movement variability is associated with healthiness. For instance, motor disabilities may be related to either (i) wide range of behaviours which appear to be random, unfocussed and unpredictable or (ii) narrow range of behaviours which seems to be rigid, inflexible and predictable. Specifically, postural sway variability which is larger for patients with Parkinson disease or the likelihood of falling in elderly individuals which is associated with too little or too much step width variability. This suggest that extremes of movement variability are symptomatic of lower ability to control movement.

1.2.1 Modelling human movement variability

Human movement involves a complex system where many sensorimotor variables such as joints, muscles, nervous system, motor unit and cells are the sources for different types of variability (Newell and Corcos, 1993). Hence, variability encompasses different types, sources and views of variability. For instance, from a biomechanical view, motion variability can be modelled as system of differential equations for the neuro-musculoskeletal control system where motion variations can occur because of "perturbations of initial states of the skeletal system", perturbations of "muscular or neural subsystems ", or "external torques and forces acting on the skeletal system" (Hatze, 1986, p. 13). According to Hatze (1986) motion variability can be caused by (i) direct consequences of adaptive learning process, and (ii) random fluctuations which are the result of stochastic processes in the nervous system. Hence, Hatze (1986) proposed measures of dispersion (e.g. Fourier series and entropy measures) to quantify the deviation of motion from a certain reference. With that, Hatze (1986) pointed out that the combination of deviations from angular coordinates (radians) and linear coordinates (meters) for Fourier series were an unacceptable quantifier as the units are different. Hence, Hatze (1986) proposed the use of entropy as a global quantifier for motion variability and concluded that any movement deviation of a body joint may be the result of deterministic and stochastic causes.

Another approach to model variability has been proposed by Müller and Sternad (2004), who decompose variability into exploration of task tolerance(T), noise reduction(N), and covariation(C). Hence, the quality of performance in goal-oriented tasks, e.g. hitting a target, is defined "by the accuracy and replicability of the results" (deviations from the target) "over repeated attempts of execution" (configuration of joint angles with its velocity, angles and position) (Müller and Sternad, 2004, p. 229). For the experiment, Müller and Sternad (2004) considered table skittles, where participants throw a ball on a string that swings around a center post with the objective of knocking down the skittle at the opposite site. Then, Müller and Sternad (2004) proposed D as the absolute average of distance to the targets in n trials and used this as a measure of the collective performance that combines a function for movement based on the execution vector with a function for the minimum distance from the target d. Therefore, the overall difference in performance D is decomposed into three unequal contributions of covariation C, noise reduction N and task tolerance T. Considering a 2-D task space that spanned the release angle α and absolute velocity v, the components of contributions of variability were calculated from five data sets (A, A_0, A_{shift}, B and B_0): (i) the component of covariation where sets A and A_0 and B and B_0 have the same means and variances, (ii) the component of tolerance where sets A and A_{shift} differ only on their location in the task space, and (iii) the component of noise where sets A_{shift} and B_0 have the same means but different variances (see Fig. 6 in Müller and Sternad (2004) for further details). With that in mind, Müller and Sternad (2004) conducted an experiment with forty-two participants for five different locations of the target skittle where for each target a participant performed 320 trials which is a total of 1600 trials and therefore presented statistical confirmation of the contributions of T, N and C using ANOVA. Hence, Müller and Sternad (2004) concluded that T and N contribute more to improvement of a performance of a task than C for initial practice, meaning that a new combination of angles and velocities explore a large region of solution space (hitting the target). However, for later practice T diminishes, and N and C started to be more relevant. Also, Müller and Sternad (2004) showed in various experiments of throwing actions that variability in the movement results (deviations from the target) is generally smaller than variability in the execution (release angles and velocities) for which it is concluded that covariation between execution variables is another component of variability. With that in mind, Müller and Sternad (2004) concluded that task space exploration is an essential contribution to the improvement of movement performances which is an explanation to the increase of noise in early practice phases.

Seifert et al. (2011) investigated coordination profiles for recreational and competitive breaststroke swimmers and proposed an hourglass model of variability that illustrates the amount of variability as a function of expertise. Hence, Seifert et al. 2011, p. 551 stated recreational swimmers show a considerable amount of intra-variability "as they seek an individually appropriate coordination pattern to accommodate the novel constrains of locomotion in water", whereas experts swimmers, after a considerable practice, will still explore new environments to optimise their technique that create another secondary blooming of variability which is the result of "the environment exploration to optimise their technique with their individual strengths (e.g. physical, anatomical, mental, etc.) and to gain an advantage over competitive swimmers". To test the hourglass model of variability, Seifert et al. (2011) considered the continuous relative phase (CRP) between the elbow phase angle and knee phase angle, therefore CRP is used as an indicator on how swimmers synchronise arm recovery (elbow extension) and leg recovery (knee flexion). Seifert et al. (2011) analysed inter-individual variability of swimmers with the shape of the curves of CRP which provide an indication of the inter-limb coordination, applied statistical measures such as hierarchical clustering using eleven variables of CRP to classify the recreational swimmers into three cluster of coordination (intermediate, most-variable and in-phase) and used Fisher information to test which CRP variables were significantly differentiated the clusters. With that, Seifert et al. (2011) concluded that inter-individual coordination variability for recreational swimmers could be the result of (i) different state of process learning, (ii) environmental constraints (different perception of the aquatic resistance), or (iii) different perception of the task constrains (floating instead of swimming).

Preatoni (2007) and Preatoni et al. (2010, 2013) report that inter-trial variability is defined as combination of functional changes associated with the nonlinear properties of the neuro-musculo-skeletal system (V_{nl}) and random fluctuations in the neuro-motor-skeletal system (V_e). Additionally, Preatoni et al. 2013, p. 72 stated that the random fluctuations in movement variability can be composed by $V_e = V_{eb} + V_{ee} + V_{em}$, where V_{eb} relates to the behavior and is the "error in the sensory information and in the motor output commands", V_{ee} is the "changes in the environmental conditions" and V_{em} is the "changes in measuring and data processing procedures". Therefore, similar as Hatze (1986), Preatoni et al. 2013, p. 77 pointed out that V_{nl} "may be interpreted as the flexibility of the system to explore different strategies to find the most effective strategy among the many available". Hence, Preatoni et al. 2010, p. 1328 concluded that the total variability represents the changes of contributions for V_e and V_{nl} and it is defined as $V_{tol} = V_e + V_{nl}$, where V_{tol} "may reveal the effects of adaptation, pathologies and skills learning". Also, Preatoni et al. (2013) noted that their work only investigated error from biological variability (e.g. V_{eb}) which does not consider non-biological noise resulting from measuring instruments or data post-processing techniques, such non-biological noise has high frequency components that are usually removed. Therefore, the work of Preatoni et al. (2010) and Preatoni et al. (2013) does not consider an overall index to quantify movement variability but the combination of both V_{eb} and V_{nl}. With that in mind, Preatoni (2007) analysed the influences of V_{eb} and V_{nl} for movement repeatability by comparing entropy measures (e.g. ApEn and SampEn) with values of their surrogate counterparts.

Generally, the previous approaches reported different models for movement variability which then are quantified with different tools. For instance, Hatze (1986) and Preatoni et al. (2010, 2013) use entropy measures as the authors consider that the origin of the signals in the human body is the result of deterministic and stochastic processes, whereas Müller and Sternad (2004) and Seifert et al. (2011) reported measures of magnitude that limited the evaluation of the whole trajectories as structures of movement variability in human body activities. Therefore, for this thesis, it is important to note that even with the proposed models for movement variability (Hatze, 1986; Müller and Sternad, 2004; Preatoni et al., 2010, 2013; Seifert et al., 2011) which have been quantified with statistical or nonlinear tools, little has been investigated with regards to the reliability of the nonlinear tools when using real-world data (Newell and Slifkin, 1998). A further review of nonlinear analysis with real-world data is presented in Chapter 2.

1.2.2 Movement variability in human-humanoid interaction

Movement variability in the context of human-humanoid interaction has been investigated for exercising, rehabilitation and dancing purposes in the last six years (Görer et al., 2013; Guneysu et al., 2015, 2014; Peng et al., 2015; Tsuchida et al., 2013). For instance, Görer et al. (2013) conducted an experiment of a robotic fitness coach where eight elderly participants performed five gestures: three for arm related exercises and two for leg strength exercises. Hence, Görer et al. (2013) with only graphical visualisation of joint angles trajectories extracted from the pose estimation of a kinect sensor, stated that only one subject out of eight fail to imitate the gestures correctly. Additionally, Görer et al. (2013) surveyed participants using a 5-point Likert scale about the positive and negative effect, flow, immersion and challenge of the human-robot interaction activity, concluding that their system is easy to use based on the high scores for immersion and positive effect and low scores for challenge and negative effect. However, the small sample size and somewhat naive analysis of data in the study makes it difficult to generalise these findings.

Another example is the work of Guneysu et al. (2014) who conducted experiments with children for upper arm rehabilitation using a play-like child robot interaction. Hence, Guneysu et al. (2014), using a Kinect sensor to get data of join angles of the participants‘ skeleton, performed an automatic evaluation of three upper body actions (shoulder abduction, shoulder vertical flexion and extension, and elbow flexion) of eight healthy children who mimicked an humanoid robot. To evaluate motion imitation, Guneysu et al. 2014, p. 202 considered similarity error using Dynamic Time Warping (DTW) that penalise large angle errors over ten percent in the area range of the motion type and applied recall measure as a representation of "how much of angular area of the baseline motion from the humanoid robot is also covered by the child's motion". Then, Guneysu et al. (2014) presented the evaluation of five physiotherapists using Intraclass correlation coefficient (ICC) which is a metric for reliability of ratings for motion types, and reported that for the first motion, which consists of only one joint, the metric and physiotherapist evaluations showed high agreement, whereas for the second and third motions, which motions were more complex consisting of more joint values, the evaluation between the metrics and physiotherapist ratings differed. Guneysu et al. 2014, p. 203 stated that during the evaluation of complicated movements, children misperceived the actions for which "therapists compensated such misunderstanding by giving high scores to the children while the proposed system only considered angles". This suggests that it is also possible that the physiotherapist' ratings differed from these data because they were considering aspects which could have been incidental to the movements. With that in mind, it is interesting to note that similarity error and recall measures with the ICC metric are not completely reliable since they did not model movements that involved more than one joint. Then, Guneysu et al. (2015) analysed movements of more than one joint of four physiotherapists performing five actions: opening a door with a key, touching the opposite shoulder with hand, taking an object from back to neck, taking an object from the back and reaching an object above the head. Guneysu et al. (2015) applied traditional statistics (e.g. sample mean and sample variance) to characterise the five actions. For instance, the initial positions of arms changed from person to person, specially for the key turning action which variation were affected by the sample mean, while performances of turning the amplitude of the arm were associated with the standard deviation of the data. However, such statistical differences cannot capture the structure of the time series from each of the participants which performed the movements at different frequencies and therefore with different data length (see Fig. 10 in Guneysu et al. (2015) for further details).

Movement variability in the context of human-humanoid interaction has also been investigated in robotic dance activities. For example, Tsuchida et al. (2013) explored four dance formations which were performed three times by nine participants who had three years of experience: dancing with a robot, dancing alone, dancing with a self-propelled robot and dancing with a projected video. To visualise dance movements, Tsuchida et al. (2013) presented two participant's movement positions with twelve trajectories each (four dance activities times three trials) of z and x directions obtained with a Kinect sensor. Although, the dance experiment was rich in terms of movement variability for both participants and dance activities, only distance between each of the conditions in the dance formation was considered. With that in mind, Tsuchida et al. (2013) concluded that the sense of dancing with a projected video of a person was the closest to dancing with a real person and the trajectory of dance with a self-propelled robot was the closest to the trajectory of a dancer. Additionally, Tsuchida et al. (2013) only applied traditional statistics (i.e., ANOVA) to characterise dance movements.

Another aspect of movement variability in the context of human-humanoid interaction is the generation of robotic dance. Recently, Peng et al. (2015) reviewed an hierarchical taxonomy of four categories for robotic dance (i.e., cooperative human-robot dance, imitation of human dance motions, synchronisation for music and creation of robotic choreography). Peng et al. (2015) pointed out that the creation of robotic dance is still an open research question because such motions should generally be both interesting and exciting for users. According to Peng et al. (2015), the creation of robotic dances can be accomplished with any of the following methodologies: (i) random generation: where robots can be programmed with series of predefined algorithms that can be chosen randomly, (ii) mapping rule: where robots can react, and therefore dance, to different factors such as colours, sounds, speech, temperature or human activity, (iii) chaotic dynamics: where chaotic systems are sensitive to initial conditions and these systems can create various dance styles from periodic and couple rhythm to jumping styles, resulting in innovative and consistent dance patterns, (iv) interactive reinforcement learning: where the robot can automatically choose motions based on rewards of participants' preferences of graceful motions, (v) evolutionary computation: in which multiple iterations of generations of dance motions can create graceful robotic dance motions, and finally (vi) using a Markov chain model, a discrete time stochastic chain, where each sequence of dance motions is considered as a state in the Markov chain producing dance that synchronise with music and emotions. While the research questions of this thesis are not focused on the creation of good robotic dances (i.e, being innovative or having accordance with human aesthetics) (Peng et al., 2015), 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 2 for fundamentals of deterministic-chaotic time series).

Although, movement variability in the context of human-humanoid interaction has not been well investigated in recent years, it can be noted that movement variability is indeed present in activities such as exercise, rehabilitation or dance. Hence, previous works in human-humanoid interaction have analysed gestures, movements or dance activities with the use of traditional statistics, however the following points show some issues in this field of research: (i) it is not clear how Görer et al. (2013) performed the evaluation of synchronisation for gestures between participants and the humanoid nor what were the methods of evaluation of gestures (apart from the visual observations to classify correct trajectories of gestures), (ii) little has been investigated with regards to the differences in movement variability of physiotherapists in the works of Guneysu et al. (2014) and Guneysu et al. (2015), and (iii) in the results of Tsuchida et al. (2013) is not clear why the distribution of trajectories for subject 1 were more uniform than the trajectories of subject 2.

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 7 for a discussion on the reasoning, as posed by (Schreiber and Schmitz, 2000), 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 2 for a review of nonlinear analysis methods with real-world data).

1.3 Research questions

A number of questions regarding movement variability have been investigated in the last decade: how is variability controlled while learning a new skill? (Bartlett et al., 2007; Seifert et al., 2011; Wagner et al., 2012), is variability associated with disease or health? (Stergiou and Decker, 2011; Stergiou et al., 2006), what are the sources of variability and how do they interact in the production of observed variation of movement? (Preatoni, 2007; Preatoni et al., 2010, 2013). Nonetheless, little has been investigated regarding to the reliability of methods of nonlinear analysis to quantify movement variability (Iwanski and Bradley, 1998; Yao and Lin, 2017) when dealing with real-world data (Bradley and Kantz, 2015; Caballero et al., 2014). Therefore, this thesis explores the effects of three methods of nonlinear analysis (e.g. Reconstructed State Space (RSS), Recurrence Plots (RP) and Recurrence Quantification Analysis (RQA)) with different features of time-series data such as structure, levels of smoothness and window lengths. To perform such exploration, two experiments were conducted with twenty right-handed healthy participants: one for human-image imitation activities and another in the context of human-humanoid imitation activities. For the experiments, participants were asked to imitate simple arm movements and participants and humanoid robot worn inertial sensors to collect time-series data. Hence, the following research questions are investigated in this thesis.

- What are the effects on RSSs, RPs, and RQA metrics of different embedding parameters, different recurrence thresholds and different characteristics of time series (structure, smoothness and window length size)?
- Additionally, what are the weaknesses and strengths of RQA metrics when quantifying movement variability?
- How does the smoothing of raw time series affect methods of nonlinear analysis when quantifying movement variability?

1.4 Outline of the thesis

This thesis is organised as shown in Fig. 1.1. Chapter 1 presents a background of quantification of movement variability, state-of-the-art for modelling human movement variability, movement variability in the context of human-humanoid interaction and research questions are stated. Chapter 2 presents an introduction to fundamentals of time series analysis in terms of: (i) what to measure in movement variability? and (ii) which nonlinear tools are appropriate to measure movement variability?, including a review of the state-of-the-art literature of nonlinear analysis with real-word data. In Chapter 3 a review of state space reconstruction method is presented that entails an explanation for uniform time delay embedding (UTDE), a description of the techniques to estimate minimum embedding parameters (e.g. false nearest neighbour and average mutual information), and an introduction to Recurrence Plots (RPs), structures of RPs and different metrics to perform Recurrence Quantification Analysis (RQA) as well as the weakness and strengthens of RPs and RQAs. In Chapter 4, the experiments for human-image imitation and human-humanoid imitation are presented describing aims, participants, activities in the experiments, equipment, ethics and preparations of the time series. Chapter 5 and 6 present the results with regards to two experiments (human-image imitation and human-humanoid imitation) for minimum embedding parameters, reconstructed state space using uniform time-delay embedding, recurrence plots, recurrence quantification analysis(RQA) metrics and 3D surfaces of RQA metrics to show the weaknesses and strengths of RQA. Finally, Chapter 7 presents conclusions, the answers for the research questions, the contribution to knowledge and future work after this thesis.

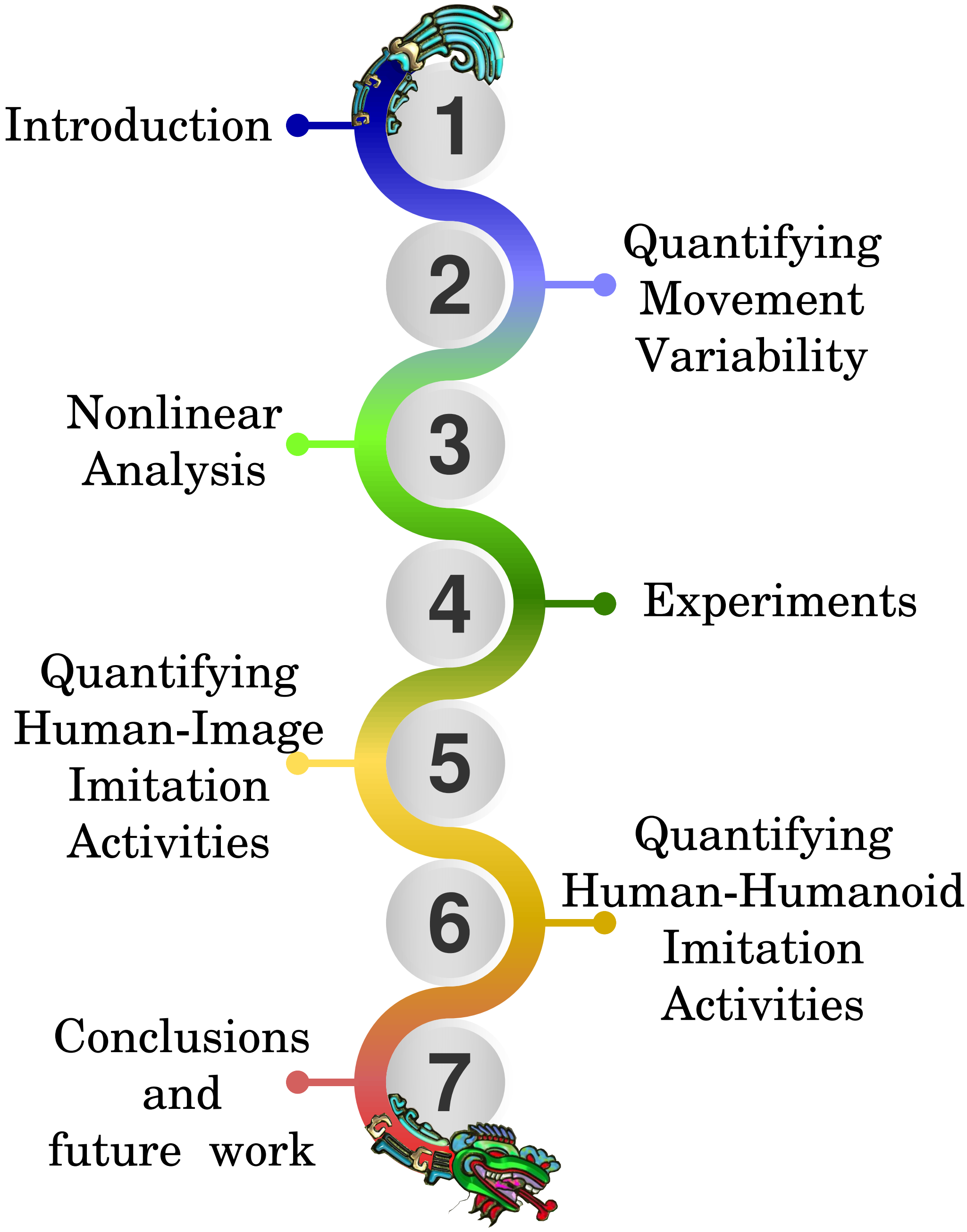

Fig. 1.1 **Thesis outline.** Chapter numbers with its titles. N.B. Quetzalcoalt, a feathered serpent, is flowing between chapters. "To the Aztecs, Quetzalcoatl was both a boundary-maker and a transgressor between earth and sky" (Quetzalcoatl, 2018).

1.5 Publications

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.

Author contributions for the papers of Miguel Xochicale (MX), Chris Baber (CB) and Mourad Oussalah (MO) are as follow: Conceptualisation: MX, CB, MO; Data Curation: MX; Formal Analysis: MX; Funding Acquisition: MX, CB; Investigation: MX; Methodology: MX; Project Administration: MX; Resources: CB; Software: MX; Supervision: CB; Validation: MX; Verification: MX; Writing - Original Draft Preparation: MX; Writing - Review: CB, MO; and Writing - Editing: MX.

- Xochicale M, Baber C, and Oussalah M. Understanding Movement Variability of Simplistic Gestures Using an Inertial Sensor. *in Proceedings of the 5th ACM International Symposium on Pervasive Displays*, Oulu, Finland, June 2016, pages 239–240. https://github.com/mxochicale/perdis2016

- Xochicale M, Baber C, and Oussalah M. Analysis of the Movement Variability in Dance Activities Using Wearable Sensors. *in Wearable Robotics: Challenges and Trends*, Segovia, Spain, October 2016, pages 149–154. https://github.com/mxochicale/werob2016

- Xochicale M, Baber C, and Oussalah M. Towards the Quantification of Human-Robot Imitation Using Wearable Inertial Sensors. *in Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, Vienna, Austria, March 2017, pages 327–328. https://github.com/mxochicale/hri2017

- Xochicale M, and Baber C. Towards the Analysis of Movement Variability in Human-Humanoid Imitation Activities. *in Proceedings of the 5th International Conference on Human Agent Interaction*, Bielefeld, Germany, October 2017, pages 371–374. https://github.com/mxochicale/hai2017.
- Xochicale M, and Baber C. Strengths and Weaknesses of Recurrent Quantification Analysis in the context of Human-Humanoid Interaction, *in ArXiv e-prints*, October 2018. https://arxiv.org/abs/1810.09249

1.6 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 https://github.com/mxochicale/phd-thesis/ (Xochicale, 2018). 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 ( ) are provided in the caption of figures in order to reproduce their results. See Appendix F for details on how code and data is organised and how results can be replicated.