Chapter 1

Introduction

1.1 Background

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

The lower dimension signals from biological data ~~signals~~ 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). Traditional methods, in time-domain or frequency-domain, 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. However, methods of nonlinear time series analysis can quantify such 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). With this in mind, 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). ~~which are explained below~~. Such method~~ologies~~s 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 ~~these~~ defined parameters may only work for one purpose, e.g., prediction, and may not work well for other purposes e.g., computing dynamical invariants (Bradley and Kantz, 2015).

In addition, the quality of the time series data affects the reliability of the results for nonlinear tools. For instance, methodologies 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 ~~have~~ be purely deterministic signals (Kantz and Schreiber, 2003). ~~Similarly,~~ Method~~ologies~~s such as RSS, RP and RQA can break down when datasets have different length, different ~~values of~~ accuracy and precision (Frank et al., 2010), or when data ~~is~~ are contaminated with ~~different or unknown sources of~~ noise (Garland et al., 2016). It is surprising that despite these problems ~~arising from the previous constraints with regard to the quality of data and the estimation of embedding parameters~~, nonlinear dynamics have proven to be helpful to understand and 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 analysis using nonlinear dynamics is the appropriate use of post-processing techniques such as interpolation, filtering or normalisation. However, there is little research on the effects of post-processing techniques in ~~the result~~ interpretation for RSSs, RPs and metrics of RQA.

1.2 Movement Variability (MV)

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 ~~a~~ 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 ~~of~~ 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).

With regard to the evaluation of healthiness, Stergiou and Decker (2011) highlighted that an optimal state of movement variability is associated with healthiness. Similarly, motor disabilities are associated with either a ~~wide range of~~ behaviours ~~such as~~ which appear random, unfocussed and unpredictable, or ~~narrow range of~~ behaviours ~~e.g.~~ which are rigid, inflexible and predictable. For instance, postural sway variability was larger for patients with Parkinson disease or the likelihood of falling in elderly individuals were associated with too little or too much step width variability. This suggests that extremes of movement variability are symptomatic of lower ability to control movement.

1.2.1 Modelling Human Movement Variability

~~The~~ Human ~~body~~ 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 (a) direct consequences of adaptive learning process, and (b) 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. ~~For which~~ Hatze (1986) pointed out that the combination of deviations from angular coordinates (radians) and linear coordinates (meters) for Fourier series were unacceptable 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). Müller and Sternad(2004) STET ~~p. 229~~ considered that 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 join ment angles with its velocity, angles and position). For the experiment, Müller and Sternad (2004) considered ~~a~~ table skittles ~~task~~, where participants throw~~ing~~ a ball ~~with~~ on a string that swings around a center post with the objective of knocking down the skittle at the opposite site. Hence, Müller and Sternad (2004) proposed D as the absolute average of distance to the targets in

n trials and ~~it is~~ used this as a measure of the collective performance that combines a function for movement~~s results~~ 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~~s~~ 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 diminishe~~d~~s and N and C start~~ed~~s 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 (variables or 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 ~~would~~ 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). ~~Then~~ 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).

~~Recently,~~ Preatoni (2007); Preatoni et al. (2010, 2013) report~~ed~~ 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 behaviour 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, ~~as~~ 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 investigate 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) do 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. → [Can you say how these measures compare? Are entropy measures as good as their models?]

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 only ~~statistics as a~~ 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 ~~either~~ statistical or nonlinear tools, little has been investigated with regards to the reliability of the nonlinear tools when using real ~~data that has the property of being~~ noisy, deterministic, stochastic or nonstationary data (Newell and Slifkin, 1998). A ~~further~~ review~~ed~~ of nonlinear ~~tools~~ methods 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.

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 join 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 ~~to the limitations of mapping human movements to a humanoid robot due to the differences in their degrees of freedom which~~ were compensated ~~with auditory feedback~~, 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~~t~~ agreement~~s~~, whereas for the second and third motions, which motions were ~~harder and~~ more complicated consisting of more joint values, the evaluation between the metrics and physiotherapist ratings differed ~~presented differences~~. Guneysu et al. 2014, p. 203 stated that during the evaluation of complicated ~~and harder~~ movements, children misperceived the actions for which "therapists compensated such misunderstanding by giving high~~t~~ scores to the children while the proposed system only considered angles". With that, it is interesting to note that the proposed metrics of similarity error and recall measure with the ICC metric are not completely reliable since they did not model well complex movements. × Recently, Guneysu et al. (2015) 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, 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. Then, Guneysu et al. 2015, p. 252 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

× Although, it is also possible that the physiotherapists' ratings differed from these data because they were considering aspects which could have been incidental to the movements.

by the sample mean, while performances of turning the amplitude of the arm were associated with the standard deviation of the data. [what does this tell us?]

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, Tsuchida et al. (2013) concluded that the sense of dancing with a projected video of a person were the closest to dance with a real person and the trajectory of dance with a self-propelled robot were the closest to the trajectory of a dancer. Additionally, Tsuchida et al. (2013) only applied traditional statistics (e.g. 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 of robotic dance (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 dances is still an open research question because dance motions should generally be both interesting and ~~exiting~~ 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 preprogrammed 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 which ~~systems~~ are sensitive to initial conditions and therefore create various dance styles from periodic and couple to 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. Therefore, while the research questions of this thesis are not fully related to the creation of good robotic dances (e.g, being innovative or having accordance with human aesthetics) (Peng et al., 2015), 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 or stochastic.

Although, movement variability in the context of human-humanoid interaction has not been directly investigated in recent years, it can be noted that movement variability is indeed applied in exercise, rehabilitation or dance. Hence, it can be noted that ~~the~~ previous work~~s~~ that has analysed gestures, movements or dance activities with only traditional statistics, for which (i) it is not ~~only~~ clear how Görer et al. (2013) performed the evaluation of synchronisation for gestures between participants and the humanoid nor ~~but also~~ what methods of evaluation, apart from the visual, ha~~s~~d been applied to classify correct gestures trajectories, and ~~whereas~~ (ii) ~~little~~ has been investigated with regards to the differences in movement of the invited physiotherapists in the work of Guneysu et al. (2014) and Guneysu et al. (2015), (iii) in the results of Tsuchida et al. (2013), it is not clear, for their results, why the distribution of trajectories for subject 1 were more uniform than the trajectories of subject 2, and (iv) even though~~t~~, the robot movements for the experiments of this thesis are simple, Peng et al. (2015) noted that generation of robotic dance movements can be done with chaotic dynamics.

Therefore, it is ~~generally highlighted~~ suggested that applying nonlinear analyses 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. Similarly, little research has been done in this context with regards to the reliability of nonlinear tools when using real-data time series (e.g. window length, post-processing techniques, noise contamination, nonstationarity, chaotic deterministic, etc).

1.3 Research questions

A number of questions regarding movement variability ~~has~~ have been investigated in the last decade (Stergiou and Decker, 2011; Stergiou et al., 2006) such as: 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 ~~recently~~ investigated ~~with regards to~~ the reliability of nonlinear tools 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 on three nonlinear tools (e.g. Reconstructed State Space (RSS), Recurrence Plots (RP) and Recurrence Quantification Analysis (RQA)) with different features of time series 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 were attached with inertial sensors that collected time series. Hence, three research questions are investigated in this thesis.

- What are the effects on RSSs, RPs, and RQA metrics ~~for~~ of different embedding parameters, different recurrence thresholds and different characteristics of time series (window length size, smoothness and structure)?

Additionally,
- ~~H~~how sensitive or robust are RQA metrics when quantifying MV?

- ~~Is it fine to smooth raw time series for the quantification of MV?~~
- What effect does smoothing the raw time data have on the quantification of MV using these techniques?

1.4 Outline of the thesis

This thesis is organised as ~~follows~~ shown in Figure 1. Chapter 1 presents a background ~~for the~~ of quantification of Movement Variability(MV) for which three research questions are raised. Chapter 2 presents an introduction to fundamentals of time series analysis ~~then it is reviewed~~ in terms of (i) what to measure in Movement Variability(MV)? and (ii) which nonlinear tools are appropriate to measure MV?, ~~and finalised with~~ including a review ~~for~~ of nonlinear analyses with real-world data. We then present in Chapter 3 a review of the state space reconstruction that includes an explanation for uniform time delay embedding and a description of the techniques to estimate of minimum embedding parameters (e.g. false nearest neighbour and average mutual information), 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 as well as the aims, participants, description of the activities in the experiments, participants, data collection from inertial measurement unit sensors, preprocessing techniques (e.g raw data, normalised data, smoothed data and windowing) equipments, ethics and preparations of the time series. Chapter ~~6~~ 5 and ~~7~~ 6 present the results with regards to the two experiments showing the computation of minimum embedding parameters, reconstructed state space using uniform time-delay embedding, recurrence plots, recurrence quantification analysis metrics and its weaknesses and strengths. Finally, Chapter ~~8~~ 7 presents the conclusions, the answer for the research questions, the contribution to knowledge and future work for this thesis.

1.5 Publications

Partial work of this thesis has been ~~published in~~ presented at the following peer-reviewed conferences.

Contributions of each authors

- 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

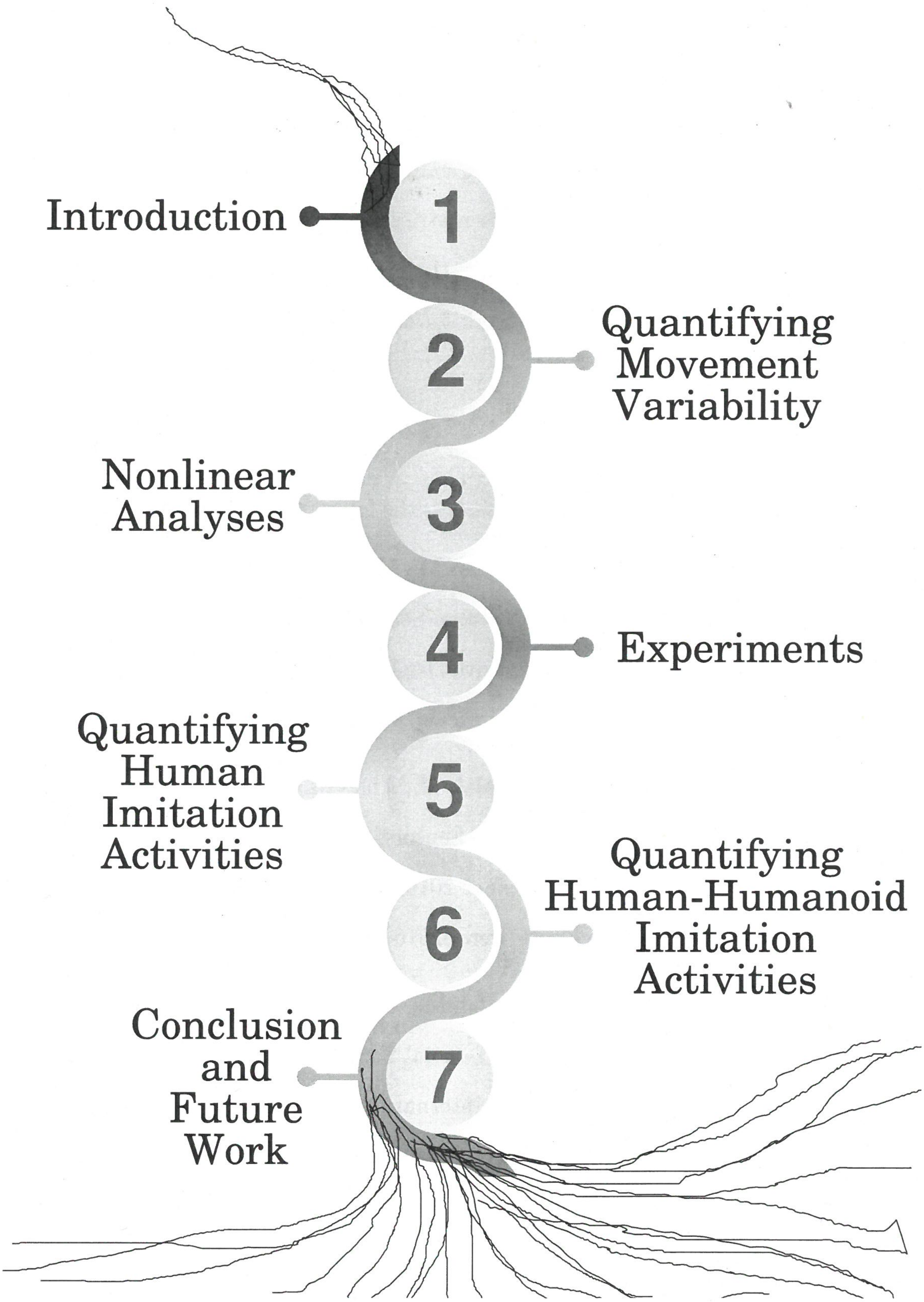

Fig. 1.1 **Thesis structure.** Chapter numbers and its titles.

Conference on Human Agent Interaction, Bielefeld, Germany, October 2017, pages 371–374. https://github.com/mxochicale/hai2017