Doctoral Dissertation

A Symbolic Approach to Human Motion Analysis Using Inertial Sensors: Framework and Gait Analysis Study

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Abstract

Motion analysis deals with determining *what* and *how* activities are being performed by a subject, through the use of sensors. The process of answering the *what* question is commonly known as classification, and answering the *how* question is here referred to as characterization. Frequently, combinations of inertial sensor such as accelerometers and gyroscopes are used for motion analysis. These sensors are cheap, small, and can easily be incorporated into wearable systems.

The overall goal of this thesis was to improve the processing of inertial sensor data for the characterization of movements. This thesis presents a framework for the development of motion analysis systems that targets movement characterization, and describes an implementation of the framework for gait analysis. One substantial aspect of the framework is symbolization, which transforms the sensor data into strings of symbols. Another aspect of the framework is the inclusion of human expert knowledge, which facilitates the connection between data and human concepts, and clarifies the analysis process to a human expert.

The proposed implementation was compared to state of practice gait analysis systems, and evaluated in a clinical environment. Results showed that expert knowledge can be successfully used to parse symbolic data and identify the different phases of gait. In addition, the symbolic representation enabled the creation of new gait symmetry and gait normality indices. The proposed symmetry index was superior to many others in detecting movement asymmetry in early-to-mid-stage Parkinson's Disease patients. Furthermore, the normality index showed potential in the assessment of patient recovery after hip-replacement surgery. In conclusion, this implementation of the gait analysis system illustrated that the framework can be used as a road map for the development of movement analysis systems.

Acknowledgments

I am sincerely and heartily grateful to my supervisors Nicholas Wickström and Thorsteinn "Denni" Rögnvaldsson, for allowing me to pursue my own ideas and to develop my own *modus operandi*. In particular, I would like to thank Nicholas for our many thoughtful discussions. I am also much obliged to the members of my support committee, Veronica Gaspes, Lars Karlsson and Boyko Iliev; and to Eva Nestius for helping me through so many administrative matters and language barriers. During the past four and a half years I have crossed paths with several people who have helped me along the way. I am truly indebted and thankful to Misha Pavel and Holly Jimison for welcoming me into their research groups and into their home in Portland, where they helped me kick start this work. I am also sincerely thankful to Fay Horak, Arash Salarian, Lars-Eric Olsson, Helene Eklund, Roy Tranberg, Roland Zügner and Wagner Ourique de Morais for their valuable contributions. This thesis would not have been possible without the help of all the people mentioned above.

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Chapter 1
Introduction

1.1 Motivation

Human motion analysis, in this thesis simply referred to as motion analysis, is a general term regarding the automatic description and/or understanding of human movements using sensors. From a technological point of view, motion analysis enables the development of innumerable applications, from computer graphics [92] to human-computer interaction [60] to health-related tele-monitoring applications [70], [32].

Motion analysis in health-related tele-monitoring applications is typically concerned with activities of daily living (ADLs), which reflect the functional status of the patient and his/her ability to care for himself/herself independently. ADLs encompass everyday activities including personal hygiene, nutrition, leisure, ambulation, work, and homemaking. The ability to walk from place to place, in particular, greatly influences the quality of life of a subject. In addition, certain walking characteristics reflect the physical [4] [18] and cognitive [31] [69] condition of patients. Therefore, gait analysis is an important aspect of motion analysis in health-related applications.

Motion analysis can be achieved through the use of fixed and/or wearable sensors. Fixed sensors are used to equip objects or structures surrounding the patient, usually in the patient's home. Wearable sensors, on the other hand, can gather information about the subject's movements independently of the environment. Most commonly, wearable systems are a combination of inertial sensors such as accelerometers and gyroscopes. Wearable systems in general, and inertial sensors in particular, are extremely important tools for motion and gait analysis, especially in health-related tele-monitoring applications. They are cheap to produce and maintain, unobtrusive so as not to interfere with daily life, and non-invasive in terms of privacy.

The main goal of motion analysis systems, in particular for health-related tele-monitoring applications, is to answer one or both of the following questions:

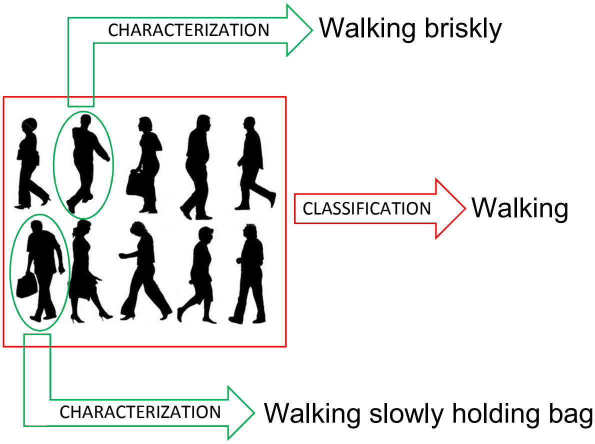

Figure 1.1: This figure illustrates the difference between classifying an activity as "walking", and characterizing that activity as "walking briskly" or "walking slowly holding a bag".

1. *What* activity is being performed?

2. *How* is the activity being performed?

The process of answering the *what* question is commonly known as classification. Answering the *how* question will be referred to as characterization. The main distinction between these two tasks is that classification groups together different instances of a movement and generalizes them into an activity. Whereas characterization aims at distinguishing the different instances or performances of one particular activity. Figure 1.1 illustrates how classification groups together the different performances of the movement under the activity "walking". Characterization on the other hand distinguishes between the different instances as, for example, "walking briskly" or "walking slowly holding a bag".

Activity classification can give great insight into the overall wellbeing of a subject. Knowing how long the subject sleeps every night or how often he/she cooks himself/herself a meal is important when making decisions about care or treatment. Activity characterization, however, can provide more detailed information about the subject's physical and cognitive condition. A sudden decrease in walking speed or a shaking hand while cooking may be early symptoms of more serious health conditions.

Although many works have addressed activity classification, little attention has been paid to movement characterization. This thesis addresses the general problem of movement characterization using inertial sensors. A method based on symbolization of sensor data and the inclusion of expert knowledge is proposed. In particular, a gait analysis application is used as a platform for exploring the characterization problem, the role of expert knowledge in motion analysis and the proposed solution. This application was chosen due to its importance in the assessment of patients.

1.2 Research Questions

1.2.1 Motion Analysis Research Questions

The majority of motion analysis systems target classification, which is typically achieved using supervised machine learning methods, *e.g.* [3] [88]. These approaches have shown excellent results, however, one important characteristic of supervised learning methods is that only a number of pre-defined activities can be identified and represented. It is important to guarantee that unknown activities also receive a representation so that new activities can be incrementally added to the system's database.

Another drawback of supervised machine learning methods is that the system is a "black box" inside which decisions are invisible to the user. Supervised machine learning methods only incorporate expert knowledge as labels in the training set. However, some unsupervised approaches have found that the inclusion of explicit expert knowledge, in the form of hierarchical decision structures, can contribute to the development of motion analysis systems [54] [21].

A few methods have tried to characterize movements using supervised machine learning methods by creating different activity classes such as walking, walking ascending stairs, walking slowly [89]. This type of characterization, however, does not allow for a quantitative comparison of movements between different subjects or before and after treatment. Another group of methods uses limb orientation tracking to describe movements in 3D space, and then compare movement kinematics between different subjects or different performances, *e.g.* [20]. Unfortunately, these methods require several sensor nodes and their description of movements relies on joint angles and angular velocities, which are difficult to interpret without visualization. Few efforts have been directed at creating data representations that facilitate characterization.

Based on the above mentioned issues, the following research questions were addressed in this thesis:

1. How to organize different approaches to movement analysis, and define characterization and classification as independent problems?

2. How can symbolization be used as an intermediate representation for motion data, which facilitates movement characterization?

3. How can expert knowledge be used to parse sensor data and facilitate its interpretation?

1.2.2 Gait Analysis Research Questions

Although motion and gait analysis systems are not usually considered side by side, gait is a typical human motion, and the motion analysis research question mentioned above also hold for gait analysis system. In addition to those, gait analysis systems have some specific characteristics that were explored in the thesis.

The majority of gait analysis systems using inertial sensors have focused on acquiring spatio-temporal variables such as cadence, stride length, speed, *e.g.* [10] [72] [75]. This information can then be used to compute spatio or temporal characterization variables such as symmetry [66] [91] or stride-to-stride variability [34]. Although spatio-temporal information is useful, it is not enough to fully characterize a patient's gait. It is possible that two subjects present the same spatio-temporal characteristics but very different kinematic characteristics.

Another common factor to most inertial gait analysis systems is that they do not generalize easily to different patient groups or different types of walk. One simple example relates to peak-detection methods used to detect heel-strike and toe-off events, *e.g.* [40] [70]. These methods do not perform well at very slow walking speeds because the peaks in the sensor data are not as prominent.

Based on the issues identified withing gait analysis applications using inertial sensors, the following is a list of the gait-related research questions considered in this thesis.

1. How can symbolization improve the characterization of different gait patterns?

2. Can signal symbolization and the addition of expert knowledge help generalize gait analysis to different walking patterns?

1.3 Research Approach

This thesis organizes motion analysis methods with respect to data representation at different abstraction levels, as illustrated in Figure 1.2. At each step of the information pyramid, the quantity of data decreases and the complexity of the information increases. At the lowest level of abstraction is the **data** itself, *e.g.* an acceleration signal. At the **information** level, the original data may be represented by certain characteristics of the signal such as frequency content, peaks, or other features. At the **knowledge** level, the system can relate the original data to certain activities or movements, *e.g.* walking, sleeping. At the **wisdom** level, the system can infer abstract concepts about these activities or movements such as "this relates to the subject's morning routine" or "the

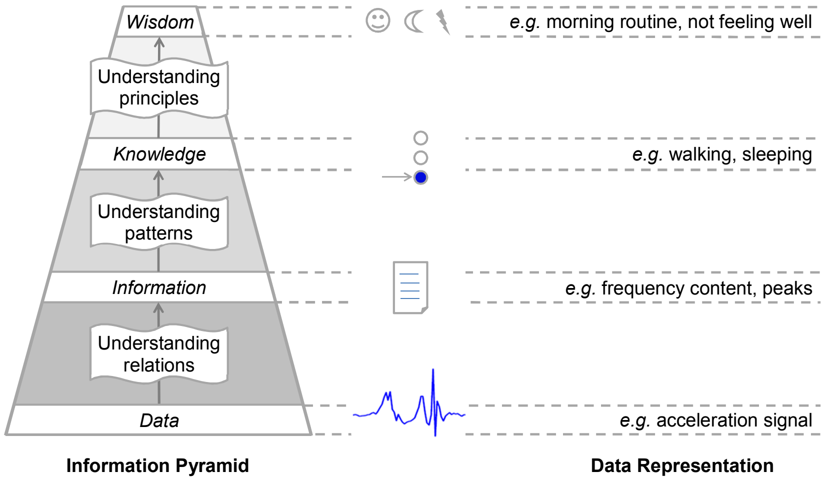

Figure 1.2: Data representation at different levels of abstraction. At each layer of the pyramid, from bottom to top, the complexity of the information increases from data, to information, to knowledge to wisdom.

patient is not feeling well". From this perspective, motion analysis systems are collections of algorithms that transform the data from one abstraction level to the next. Based on this data representation structure, a framework was created to address the issues mentioned previously.

The proposed framework is based on symbolization of the sensor signal. The main idea behind this symbolic approach is that the original signal can be segmented into building blocks. These building blocks can then be combined to represent different movements or activities, similarly to how letters in the alphabet are combined into words.

Potential solutions to the general problems highlighted previously were investigated within the smaller domain of gait analysis. Gait analysis was chosen because it is a well-defined task of great importance to health-related applications. Furthermore, walking is a well-understood movement and the periodicity of this activity facilitates its analysis.

The steps taken to address the proposed research questions were:

1. **Proposal:** To create a framework for organizing motion analysis approaches with respect to different levels of data abstraction, identify the shortcomings of current approaches and position the symbolic approach within the framework;

2. **Technical assessment:** To investigate the feasibility and usefulness of the proposed approach within the field of gait analysis;

3. **Applied assessment:** To investigate the expressiveness and usefulness of the symbolic representation in a clinical environment.

1.4 Contributions

The main contributions of this thesis can be summarized as follows:

1. The introduction of a general framework that organizes and situates different motion analysis methods with respect to data at different levels of abstraction.

2. The proposal of a symbolic approach for motion analysis within the framework. The approach enables general representation of movements, motion characterization independently of classification, as well as the inclusion of expert knowledge.

3. A proof of concept implementation of the framework for motion analysis, which specifically addresses gait analysis. The proposed approach was used to identify and detect the phases of gait; expert knowledge was used to parse symbolic sensor data; and walking pattern characterization was achieved independently of classification or labeled data.

4. The introduction of a symbol-based similarity measure that was used to assess both movement symmetry and gait normality. This measure of symmetry was shown more effective than other measures in identifying Parkinsonian symptoms. The symmetry and normality measures correlated well with 3D kinematic data. The normality measure also showed potential for assessing patient recovery in a clinical environment.

5. The evaluation and comparison of different symbolization techniques. Temporal segmentation and quantization methods were evaluated based on compression capabilities and loss of information. Results indicated that temporal segmentation methods, if properly initialized, can segment periodic signals better than quantization methods. However, quantization is more consistent and reliable on a large variety of signals.

1.5 Publications

Summary

This thesis is mostly based on five selected publications. The following is a summary of how the included publications relate to each other and to the research questions addressed in this thesis.

1. In **Paper I** the validity of the framework was explored within a gait analysis application. The symbolic approach was used to identify and detect gait events and also derive a new measure of gait symmetry. This paper describes how prior knowledge can be incorporated into the analysis in order to parse the symbolic data. Furthermore, the proposed measure of symmetry was shown more informative than traditional spatio-temporal symmetry measures.

2. Propelled by positive initial results, **Paper II** further investigated the properties of the proposed symmetry measure in comparison to six other commonly used symmetry indices. The main objective of this study was to explore the advantages of the symbolic representation for clinical applications. The chosen application was a measure of movement symmetry in early Parkinson's Disease patients. Results showed that, on the data used in this study, the proposed symmetry measure was more informative and more sensitive to Parkinsonian symptoms. Another advantage of the proposed method was that it could be used to describe the symmetry of both lower and upper limbs during walking.

3. A fundamental aspect of the suggested framework is symbolization. Therefore, **Paper III** aimed at answering the question: what is the best way to symbolize inertial sensor data? A brief comparison of three symbolization methods on 47 different signals was conducted. Although this study did not settle the question, it provided valuable insight into the advantages and disadvantages of different symbolization methods.

4. Inspired by the symmetry measure, a measure of gait normality was created based on the same symbol-based representation. This normality index compares the subject's data to a reference data set of healthy gait patterns. The goal of this normality measure was to provide a quality of gait index that was easy to interpret and helpful in the assessment of patients. **Paper IV** reports the evaluation of both symmetry and normality indices against 3D kinematic data.

5. The natural continuation was to investigate if these measures were indeed relevant and helpful in a real clinical environment. The symbolic measures of symmetry and normality were used to evaluate the quality of gait of hip-replacement patients. These two measures were also compared

to quantitative and qualitative measures of patient recovery. This work is reported in **Paper V**.

Appended Publications

Table 1.1 lists the five selected publications included in this thesis. The main author of each paper is underlined.

Table 1.1: List of appended publications

Paper I	A. Sant'Anna, and N. Wickström. A symbol-based approach to gait analysis from acceleration signals: identification and detection of gait events and a new measure of gait symmetry. *IEEE Transactions on Information Technology in Biomedicine*, 14(5):1180-1187, 2010.
Paper II	A. Sant'Anna, A. Salarian, and N. Wickström. A new measure of movement symmetry in early Parkinson's disease patients using symbolic processing of inertial sensor data. *IEEE Transactions on Biomedical Engineering*, 58(7):2127-2135, 2011.
Paper III	A. Sant'Anna, and N. Wickström. Symbolization of time-series: an evaluation of SAX, Persist, and ACA. In *Proceedings of the 4th International Congress on Image and Signal Processing (CISP)*, 4:2223-2228, 2011.
Paper IV	A. Sant'Anna, N. Wickström, R. Zügner, and R. Tranberg. A wearable gait analysis system using inertial sensors Part I: evaluation of measures of gait symmetry and normality against kinematic data. In *Proceedings of the International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC)*, 2012 (*in press*).
Paper V	A. Sant'Anna, N. Wickström, H. Eklund, and R. Tranberg. A wearable gait analysis system using inertial sensors Part II: evaluation in a clinical setting. In *Proceedings of the International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC)*, 2012 (*in press*). Received Best Student Paper Award.

Other Publications

Table 1.2 presents a list of related publications that will not be explicitly included in this thesis because they are a subset of the work presented in the five appended publications.

Table 1.2: List of related publications

A. Sant'Anna, and N. Wickström. A linguistic approach to the analysis of accelerometer data for gait analysis. In *Proceedings of the 7th IASTED International conference on biomedical engineering*, 2010
A. Sant'Anna, and N. Wickström. Developing a motion language: gait analysis from accelerometer sensor systems. In *Proceedings of the 3rd International conference on Pervasive computing technologies for healthcare*, pages 1-8, 2009
A. Sant'Anna, W. de Morais, and N. Wickström. Gait unsteadiness analysis from motion primitives. *Gerontechnology*, 7(2):204, 2008

1.6 Outline

The rest of the thesis is organized as follows. Chapter 2 introduces related work in motion analysis, the symbolic approach and the proposed framework; Chapter 3 introduces the gait analysis scenario, related work and the framework implementation; Chapter 4 summarizes each appended paper; Chapter 5 discusses limitations and possible future research directions, summarizes and concludes the thesis.

Chapter 2
Motion Analysis

Motion analysis is an important component of systems targeting health-related applications such as assisted physiotherapy at home [78], computer interface for disabled persons [60], automatic detection of falls in the elderly [85], among many others. The goals of motion analysis may be generalized as *classifying* movements and activities, or *characterizing* movements and activities.

Inertial sensors such as accelerometers and gyroscopes are a common and appropriate choice of sensors for motion analysis systems. They are low cost, small, non-invasive in terms of privacy and can be easily integrated in clothing or garments such as watches and belts. In addition, most mobile phones are equipped with a set of inertial sensors that can provide very cheap and ubiquitous motion analysis systems, *e.g.* [13].

This chapter concerns motion analysis methods using inertial sensors. The remaining of this chapter will review related works in motion analysis and identify their shortcomings; discuss how the symbolization of sensor data may help address such issues; and introduce a framework for motion analysis based on symbolization.

2.1 Related Work

Inertial sensors such as accelerometers and gyroscopes have been shown appropriate for measuring a variety of human movements, *e.g.* estimating limb orientation [38], [20]; measuring body posture [84]; measuring energy expenditure [37]; detecting and interpreting gestures [41], [79]; activity and context recognition [54], [42], [88]; among others.

Many techniques have been used to classify activities using inertial sensors. The first step is usually feature extraction, where certain temporal and/or frequency characteristics are extracted from the data. These features are then used to classify activities, mostly based on supervised machine learning methods such as k-nearest neighbor [3]; hidden Markov models (HMM) [36]; artificial neural networks (ANN) [3], [88]; support vector machines (SVM) [3], [88]. These approaches have shown excellent results. However, one important characteristic of supervised machine learning methods is that the representation of activities is only possible for a number of pre-defined activities, which have been previously studied and labeled. In addition, these methods are difficult to modify or update. The addition of a new class of activities, for example, requires a new data set and/or retraining of the entire system.

Another characteristic of most supervised machine learning methods is that they result in a "black box" inside which decisions are made invisible to the user. This is particularly troublesome for health-related applications, where understanding the reasoning behind a given decision is extremely important for its validation. That is, knowing a patient has been judged unwell is not sufficient, it is important to know that this decision was made based on, for example, lack of sleep.

A few unsupervised approaches have also been investigated for activity classification, such as hierarchical methods [54] [21] and self-organizing maps (SOM) [43]. Hierarchical methods are binary decision structures consisting of a number of consecutive nodes. These decision structures are designed based on expert knowledge and manual inspection of training data. The classification decisions are therefore transparent to the user. Nonetheless, the performance of the system relies on the human expert who designs the decision tree. SOM methods analyze and cluster the data based on feature similarities, without the need for labeled training data. This procedure is useful for exploring and investigating characteristics of the data set, however, an extra supervised layer is needed to achieve the complete classification task [43]. Hybrid models that combine the expert knowledge of hierarchical models and the non-linear classification process of ANN have been shown to improve the performance of activity classification systems [21]. A more detailed review of activity classification methods can be found in the article by Preece *et al.* [67].

Some movement characterization has been attempted based on supervised machine learning methods, by specifying activity classes such as walking, walking ascending stairs, walking slowly [89]. This type of pseudo-characterization, however, does not allow for the comparison of movements between different subjects, or before and after treatment. More accurate characterization may be achieved by using limb orientation and tracking methods to describe movements in 3D space, and then compare movement kinematics, *e.g.* [20]. These methods, however, are relatively complex and make use of several sensor nodes. In addition, the characterization of movements in the 3D space relies on the description of angles and velocities, which are difficult to interpret without visualization. There is room for improving movement characterization methods. One possible way to achieve this is to create a data representation scheme tailored for characterization tasks, instead of going through 3D space and kinematic information.

2.2 Symbolic Approach

One way to address the challenges mentioned previously is to use a different representation scheme for the data. That is, to transform the original motion signal into something more versatile. One way to achieve this is through symbolization, that is, to break-down the motion signal into elementary building blocks. The analysis of the signal then investigates how these building blocks interact with each other, and how they can be combined to express different movements, similarly to how letters are combined to form words.

Symbolization is an efficient way of extracting information about the underlying dynamics of time-series. Symbolic interval time-series, for example, has been shown an appropriate data format for discovering temporal knowledge that can be easily communicated to humans through linguistic expressions [83], [59]. An important practical advantage of working with symbols is that the efficiency of numerical computations is greatly improved through compression. Furthermore, symbolic data is often less sensitive to noise in measurements [19]. Another advantage of using time-series symbolization is that it widens the pool of available data mining and analysis methods to include the fields of text processing, bioinformatics, knowledge representation, among others. In addition, there are many techniques that are only defined for symbolic data such as Markov models, suffix trees, and decision trees [51].

Some works have already considered the use of symbolization for motion analysis. Fihl *et al.* [24] represented video sequences of arm movements as strings of primitive motion symbols. A probabilistic edit distance was then used to measure the difference between a given string and known motion sequences. Guerra-Filho and Aloimonos [30] symbolized joint angle displacement signals and created a context-free grammar for describing different activities using symbols. Mörchen and Ultsch [59] measured a combination of symbolized electromyography, inertial sensors and foot contact sensor signals from a subject during in-line skating. The temporal relations between symbols were characterized and a meta rule was derived to express, in words, what actions were involved in the activity, based on the symbolized sensor data. So far, except for the work described in this thesis, no symbolic approaches have been introduced for movement analysis using only inertial sensors.

2.3 Framework

As mentioned previously, data may be represented at different levels of abstraction. One way to visualize the different abstraction levels is with the information pyramid shown in Figure 1.2, where the refinement of the information increases at each step, from data to information to knowledge to wisdom. The

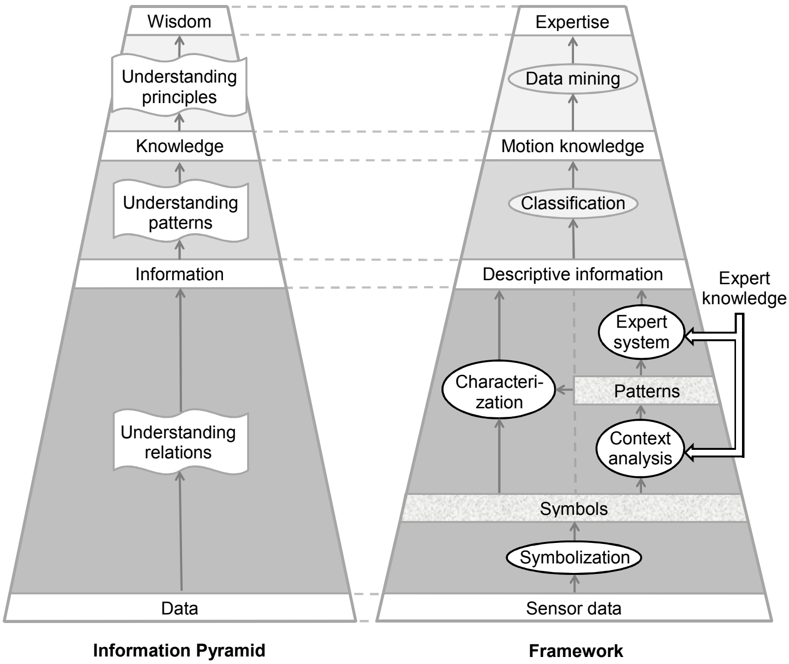

Figure 2.1: This figure illustrates how the sensor data may be manipulated in the framework from one level of abstraction to the next, and how it corresponds to different abstraction levels in the information pyramid. The framework consists of four general processes: symbolization, context analysis, expert system and characterization.

framework described here is a suggestion on how to transform the data from one level to the next, as illustrated in Figure 2.1.

The proposed framework consists of four general processes: **symbolization**, **context analysis**, **expert system** and **characterization**. **Symbolization** creates an intermediate data representation: symbols. The relationships between symbols are investigated through **context analysis**. These relations may be expressed through patterns, sequences of symbols, or rules. The **expert system** is responsible for mapping patterns or symbols to human concepts or linguistic descriptions of the system. Symbols and patterns can also be directly used to **characterize** different aspects of the movement, independently of expert knowledge.

This thesis will focus on the first two layers of the framework pyramid in Figure 2.1. The top two layers in the framework pyramid are only examples of how the highest abstraction levels may be achieved. The purpose of this figure is to provide a slightly more concrete visualization of how different framework processes relate to each other and to the different abstraction levels of the information pyramid.

2.3.1 Example

The following is a very simple example illustrating the different processes in the framework. Imagine that a patient's activities are to be monitored after surgery in order to determine how active the patient is during recovery. The patient can be monitored using a 1-axis accelerometer attached to a belt. The static posture of the subject can be easily extracted from the accelerometer based on whether the gravitational acceleration component is parallel or perpendicular to the accelerometer axis [81].

The sensor data is therefore an acceleration signal. The **symbolization** of the signal can be achieved by segmenting the signal into static and dynamic activity periods, and identifying moments when the patient is lying down. The original acceleration signal can then be converted into a temporal sequence of symbols relating to "lying-in-bed" or "out-of-bed". This corresponds to the bottom layer in the framework pyramid in Figure 2.1.

The second layer in the framework pyramid in Figure 2.1 can be divided in two. The right side relates to processes that incorporate expert knowledge, namely **context analysis** and **expert system**, whereas the left side deals with **characterization**.

Context analysis identifies patterns or structures in the symbolic data. In this example, patterns may be certain sequences of "lying-in-bed" and "out-of-bed" that repeat daily. Perhaps the symbolic data reveals that there is always at least one instance of "out-of-bed" after 9 am, and at least one long instance of "laying-in-bed" after 1 pm.

Now that certain patterns of interest have been identified, their meaning may be determined by including expert knowledge. It may be known for example, that the patient normally has lunch some time between 11:30 am and 1 pm. It may also be known that a nurse or family member visits the patient for at least one hour every afternoon. The **expert system** is the process that makes the connection between patterns in the symbolic data and expert knowledge. This connection may result in detecting "out-of-bed" symbols that indicate "lunch" or "with-carer". At this level of abstraction the data conveys information about the patient's daily activities.

The left side of the second layer in the framework pyramid in Figure 2.1 converts symbols to information through **characterization**. This process typically quantifies certain aspects of the symbolic data. In this example, characterization could be a simple accumulation of the time spent "out-of-bed" to determine on average how many hours the patient is active every day. This characterization of the patient's activities can be used to compare the patient's well-being before and after treatment, or determine the rate of recovery of the patient.

The third layer in the information pyramid in Figure 2.1 is concerned with converting information into knowledge. One common way to achieve this is through classification. In this example, one possibility would be to determine whether or not the patient is in good health. This could be decided based on how much time he/she spends out of bed or how far from a typical day he/she is having.

The last layer in the information pyramid in Figure 2.1 transforms knowledge into expertise. One possible way to achieve this is through data mining. In this example, data mining could be used to determine how active the patient must be in order to recover as soon as possible. This level of understanding uncovers certain basic principles or properties of the system under study.

2.3.2 Discussion

Note that in this framework, as opposed to previous motion analysis methods, both classification and characterization may be achieved independently. The position of these two tasks within the framework reflect the abstraction level of the information they produce. That is, characterization conveys more detailed information compared to classification, which in turn generalizes activities to a higher level of abstraction. This does not mean that characterization is a sub-problem of classification, nor that classification depends on characterization. They are, in reality, two different and independent problems.

One of the most sensitive points of the framework is symbolization. It is the basis for the framework, and it affects all subsequent steps. An ill-chosen symbolization technique may cause chain reactions or accumulated errors throughout the processes. Similarly to symbolization, a poorly constructed expert system will not add any value to the framework.

Another important characteristic of the framework is that any signal can receive a symbolic representation, independently of pre-defined features or activities. The interpretation of symbols and refinement of information relies on expert information. However, the absence of expert knowledge does not prevent the characterization of movements nor the representation of movements as symbolic strings.

The modular nature of the framework allows for several different implementations and combinations of methods. The overall system may be improved incrementally by adding new methods or making small modifications. The expert system, in particular, can be incrementally grown to incorporate newly discovered or more complex rules. The addition of expert knowledge means that basic knowledge about the system does not have to be extracted from data, but it can be directly incorporated by a human expert, without the need to collect new data. Another advantage of the expert system is that it provides an intuitive way to match sensor data to human concepts.

2.4 Summary

The research gaps in motion analysis using inertial sensors can be summarized as follows:

1. The majority of motion analysis methods deals with classification only;

2. Most motion analysis systems, based on supervised machine learning methods, are difficult to modify or update, and result in "black-box" systems;

3. Characterization methods, based on reconstructing 3D kinematics, require many sensor nodes and are difficult to visualize and quantify.

Symbolization methods may help address the above mentioned issues by providing a more versatile representation for the sensor data. Symbolization may also help reduce the effect of noise and facilitate the recovery of important movement dynamics from the data [19]. Symbolic representations of movement have been successfully used for mocap [30], video [24], and electromyography (EMG) [59] data. The framework proposed here concerns the use of a symbolic representation for inertial sensor data.

The main characteristics of the proposed framework are summarized bellow:

1. The framework can characterize different movements independently of classification;

2. The representation of data in the framework is not limited to pre-defined activities;

3. The framework takes advantage of expert knowledge to parse the data and extract relevant information;

4. The framework facilitates the interface between sensor data analysis and human experts, by identifying the meaning of different symbols and by making the decision process transparent.

Chapter 3
Gait Analysis

Walking is an important activity and can reflect several aspects of a patient's cognitive and physical health. Gait analysis is recognized as an essential part of medical assessment for a number of conditions. However, it is not routine practice due to costs involved in creating and using gait labs. Alternatively, inertial sensors can be used in the development of cheap and wearable gait analysis systems. Inertial sensors are cheap, and easy to embed into garments such as shoes. They provide means for unobtrusive and continuous acquisition of important gait information.

This chapter starts by illustrating the importance of quantitative gait analysis as a patient outcome. Then, background and related work are discussed. Finally, an implementation of the proposed framework for gait analysis is presented.

3.1 Scenario

Imagine that the orthopedic ward of a hospital would like to quantitatively and objectively measure the improvement of patients after hip-replacement surgery. A quantitative measure of improvement enables, for example, the optimization of resources on a patient by patient basis. The development of reliable patient outcome indicators is also important for assessing the quality of care provided at the ward [53]. In addition, this type of measurement supports patient empowerment [6], enabling patients to make decisions about their post-operative treatment based on objective information.

Patient outcomes in hip replacement are usually measured with self-reported questionnaires such as the SF-12 and the Oxford Hip Score [63]. These questionnaires subjectively evaluate the patient's health status with respect to pain, physical and mental condition. Many of the questions relate to mobility and the ability to perform normal daily activities. Although pain and mental condition are subjective by nature, an objective outcome measure of mobility can be developed using motion analysis.

The level of mobility of a patient may be inferred from the activities he/she performs or it may be derived from how well the patient walks. The first option infers the level of mobility of the patient by monitoring, for example, how many minutes the patient walks per day, or how much time the patients spends in bed. This type of activity monitoring can help determine empirically the level of mobility and the quality of life of the patient. The second option is to assess the quality of the patient's walk from more specific characteristics such as speed, symmetry, balance, among others. This process is generally referred to as gait analysis. The advantage of gait analysis over activity monitoring is that it provides not only general information about how mobile the patient is but also specific information on how the surgery has affected the patient's gait.

Generally speaking, the goal of gait analysis can be to determine if a subject's gait is pathological or normal. Or to assess how different a subject's gait is from a given reference, be that reference a previous assessment or a reference of normality. These two tasks will be referred to as classification and characterization respectively.

3.2 Related work

3.2.1 Gait Analysis

Gait is usually studied in three different domains: kinetic, kinematic and spatio-temporal. Kinetics investigates the forces involved in producing the movements necessary for walking. These are usually calculated from ground-reaction forces that are mapped upwards through lower limbs and joints based on biomechanical models. Kinematics investigates the movement of the body through space. The position and movement of each body segment is usually transformed into angular displacements of joints over time. Spatio-temporal methods are based on temporal variables such as cadence, and spatial variables such as stride length. One can imagine that spatio-temporal variables can be acquired from foot prints over time. Figure 3.1 illustrates the three different feature domains for gait analysis.

The state of the art in gait analysis involves a combination of motion capture (mocap) system and force plates, which can measure kinematic and kinetic variables respectively during walking. From this dataset other kinetic, kinematic and spatio-temporal variables may be calculated with the help of biomechanical models. Unfortunately, such systems are expensive, difficult to interpret, and cannot be made available to all patients [77]. As an alternative, inertial sensors may be used to create cheaper, wearable gait analysis systems. Inertial systems are relatively cheap, and can be easily deployed independently of the environment. They are not as accurate as mocap systems but can provide valuable quantitative information to aid patient assessment. In addition, they may be used to continuously monitor patients at home.

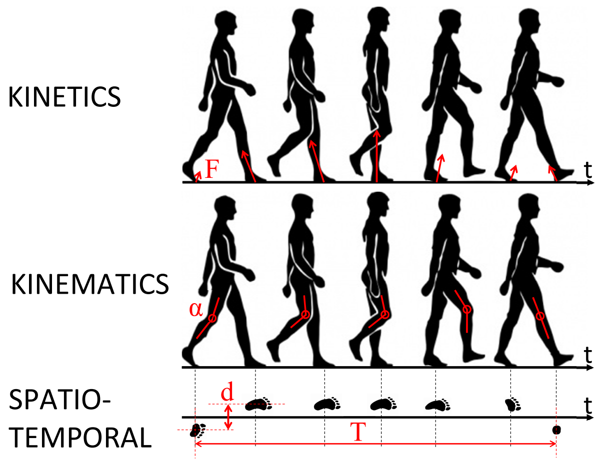

Figure 3.1: The different feature domains for gait analysis: kinetic, kinematic and spatio-temporal domains.

3.2.2 Inertial Sensors Systems

The several different approaches to gait analysis using inertial sensors may be organized according to the type of information they convey: spatio-temporal or kinematics. Kinetic information cannot be acquired with inertial sensors.

The most common inertial gait analysis systems described in the literature aim at recording spatio-temporal variables. Many studies have found that inertial sensors can provide valid and reliable measures of phases of gait [45] [29]; walking speed, cadence, stride length and other spatio-temporal parameters [72] [16]; as well as symmetry and stride-to-stride regularity [75]. Although spatio-temporal information can be very useful, it does not represent the subject's gait pattern as a whole [17].

The second group of inertial systems encompasses those that are able to extract kinematic information such as joint angle progressions, segment rotations and accelerations, *e.g.* [20], [25], [23]. These systems can provide an inexpensive alternative to in-lab 3D gait analysis. However, proper training and experience are required for interpreting this kinematic information. In addition, these systems require a larger number of sensors and are too cumbersome to be used for extended periods of time.

Alternatively, less obtrusive systems have been developed for measuring the kinematics of the body's center of gravity instead of the kinematics of lower limbs. These systems directly measure more general characteristics of gait such as gait symmetry [28], gait regularity [57], and balance [2], [55]. These general characteristics of gait are usually not enough for determining the cause of a subject's gait abnormality, but they are easy to interpret and can be used to monitor the subject's progress and recovery.

A factor common to most of these methods is that they are tailored to specific applications and do not generalize easily. For example, many spatio-temporal methods use peak detection for determining heel-strike and toe-off, *e.g.* [70], [40]. This works very well when subjects walk at normal speeds, however, this method might not be appropriate for measuring frail elderly subjects or surgical patients who walk very slowly and shuffle their feet. Another example can be found among kinematic methods that combine acceleration and gyroscope data to determine the angular position of limbs, *e.g.* [20]. These techniques are constrained to moments when the acceleration is low, normally during stance. This works well for walking but might not work for running.

One reason why most methods cannot be easily generalized is because they incorporate expert knowledge implicitly as *ad hoc* processing or in biomechanical models. It is possible that by explicitly incorporating expert knowledge, the system can automatically adapt to new data sets or new applications.

Incorporating expert knowledge explicitly can also make systems more transparent to clinicians. Very often the decisions taken by classification systems, or the variables used to characterize gait patterns, are only understood by the creator of the system or clinicians experienced in gait analysis. The acceptance of new gait analysis systems, by healthcare staff and patients, will be greater if they are intuitive to use and if results are easy to understand.

3.3 Implementation

Motivated by the scenario presented at the beginning of this chapter, the proposed framework was used to create a gait analysis system. In addition to the general issues explored by the framework; i.e. the characterization of movements independently of classification, and the use of expert knowledge to improve data analysis and interface with the user; the gait analysis system was also concerned with characterizing gait with information additional to spatio-temporal variables, and generalizing its analysis to very different walking patterns.

Another requirement was that the system should contain the minimum number of sensors possible, which should be quick and easy to wear. A small number of sensors is important in order not to interfere with the patient's behavior. It also facilitates usage and ensures better compliance from both patient and staff undertaking the analysis. Ease of use is important to ensure that the operating staff does not require complex additional training.

Throughout the five appended papers, three sensor positions were investigated: the outside of each shin just above the ankle, Figure 3.2; the waist line immediately below the navel, Figure 3.3; and the dorsum of each wrist, Figure 3.4. The waist sensor could have been placed on the patient's lower back. However, due to a parallel study where patients wore one sensor node continuously throughout the day, it was determined that the frontal position was more comfortable for the patients, who spent a lot of time in bed.

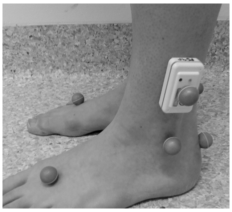

Figure 3.2: Ankle sensor position

Figure 3.3: Waist sensor position

Figure 3.4: Wrist sensor position

In addition, different combinations of inertial sensors were used. The sensor nodes varied from 3-axis accelerometers, to combinations of 3-axis accelerometers and 3-axis gyroscopes, to combinations of 1-axis and 2-axis gyroscopes. In order to cope with eventual changes in sensor orientation, and to make the analysis of the sensor data more uniform, sensors with more than one axis had their data combined into a resultant signal. That is, each 3-axis sensor, accelerometer and gyroscope alike, had its data converted into a unidimensional signal according to the formula $S_{res} = \sqrt{S^2_{axis1} + S^2_{axis2} + S^2_{axis3}}$. Similarly, each 2-axis sensor had its data converted to $S_{res} = \sqrt{S^2_{axis1} + S^2_{axis2}}$. These resultant signals were then used in the data analysis.

The remaining of this section discusses how the different parts of the proposed framework were implemented in the gait analysis system, namely symbolization, context analysis, expert system, and characterization.

3.3.1 Symbolization

Symbolization of the continuous sensor data is the foundation for the proposed framework. This is the process represented at the bottom of the framework pyramid, as illustrated in Figure 3.5.

An unavoidable part of the symbolization process is the segmentation of the signal. Time-series segmentation can take place in two domains: the amplitude or the temporal domain. We will refer to the former as quantization, and to the latter as temporal segmentation. Figure 3.6 shows a very simple example of each type of segmentation. Symbolization after quantization is very straight forward, an unique symbol is assigned to the segments in each quantization interval. Symbolization after temporal segmentation involves clustering similar segments into classes, which are then assigned a symbol.

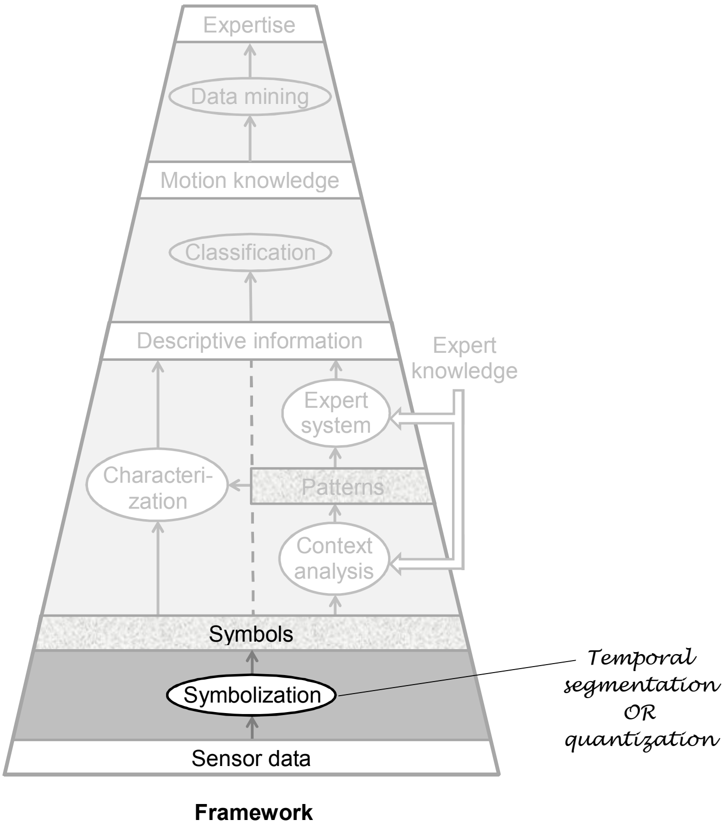

Figure 3.5: The symbolization process within the framework. Symbolization depends on segmentation, which can be achieved through temporal segmentation or quantization.

Several segmentation methods were investigated during the course of this research. In **Paper I**, a temporal segmentation method was used. The resultant acceleration signal was segmented according to a piecewise linear approximation. Each linear segment was identified by a group of features and these feature vectors were k-means clustered into symbol classes. Although this approach presented good results, the clustering method was too dependent on initialization and hard to replicate.

In **Paper II**, a quantization approach was chosen in order to overcome the clustering issue. The Symbolic Aggregate Approximation (SAX) method [51] was used with good results. The issue with SAX is that it assumes that the signal is normally distributed, and the quantization breakpoints were chosen based on equiprobable partitions of a normal distribution.

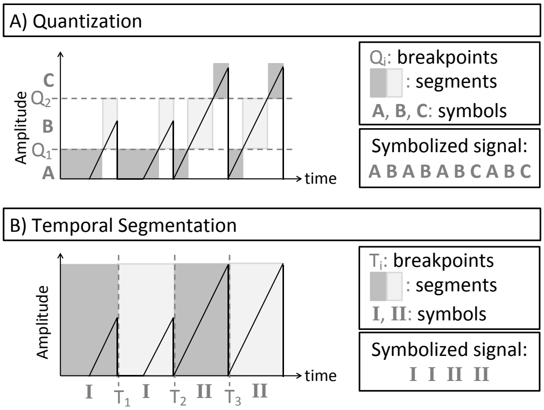

Figure 3.6: This simple example illustrates the main differences between quantization (A) and temporal segmentation (B). The breakpoints of quantization are in the amplitude domain, and each interval may be assigned a symbol. The breakpoints of temporal segmentation are in the temporal domain, and similar segments must be clustered before they can be assigned a symbol.

In order to investigate the properties of quantization and temporal segmentation methods, a comparative study was undertaken, and reported in **Paper III**. The hypothesis was that periodic signals were better segmented along the temporal domain whereas random signals were better segmented along the amplitude domain. Two quantization methods and one temporal segmentation method, developed by other research groups, were investigated on 47 distinct signals.

In addition to SAX, PERSIST was chosen as a quantization method [58]. PERSIST tries to identify different states of the system under observation and assign them different symbols. This is achieved by segmenting the signal so as to optimize the persistence of the resulting symbols. This measure of persistence is based on the Kullback-Leibler divergence [44] of the marginal and self-transition probability distributions of the resulting symbols.

The temporal segmentation method chosen for comparison was the Aligned Cluster Analysis (ACA) [90]. This is a method for unsupervised clustering of temporal patterns in mocap data. ACA is an extension of kernel k-means clustering [73] that allows for variable numbers of features in each observation. In addition it uses a distance metric based on Dynamic Time Alignment Kernel (DTAK) [76], which is robust to noise and invariant to the speed of the action.

As suggested by the hypothesis, ACA performed extremely well on certain periodic signals. However, its overall performance was inconsistent due to large variability in the segmentation and clustering parts of the method. Similarly, SAX outperformed the other methods on some low periodicity signals, but not on all signals of the same group. SAX and PERSIST performed very similarly but SAX presented slightly better results overall.

Based on SAX, a new quantization method was introduced in **Paper IV** and again used in **Paper V**. Similarly to SAX, the breakpoints were chosen so as to produce equiprobable symbols. However, the signal distribution was not considered Gaussian but estimated based on the *a posteriori* distribution of the signal. The motivation for introducing this new segmentation method was that, although SAX presented some clear advantages over the other methods, the distributions of the sensor signals were very different from a Normal distribution.

Although several techniques have been investigated, by no means have all options been exhausted. Many other symbolization techniques are possible, such as quantization method based on signal statistics, or temporal segmentation methods based on motif discovery.

3.3.2 Context Analysis

Context analysis is one of the processes represented on the right side of the framework pyramid as shown in Figure 3.7. This part of the framework investigates, guided by expert knowledge, how symbols or sequences of symbols relate to other symbols. The development of this part of the framework is reported in **Paper I**, where three known aspects of gait were used for this analysis: periodicity, the relative duration of stance, and the right-side-left-side relations in walking.

Periodicity was used to identify potentially interesting symbols that corresponded to certain events in the signal. The hypothesis was that symbols that occur approximately once every cycle have a higher chance of corresponding to relevant aspects of gait. Based on the overall periodicity of the signal and symbols, relevant symbols were identified.

The following step was to determine whether any of these relevant symbols could correspond to heel-strike (HS) or toe-off (TO) events. For that, pairs of relevant symbols were created as potential HS and TO representatives. For each pair, stance times and stride times were calculated throughout the signal as if these symbols really corresponded to HS and TO. If the calculated average stance time was more than half of the average stride time, the pair was considered a plausible candidate for HS and TO.

The right-side and left-side context analysis investigated if these plausible pairs of symbols also fulfilled the requirement that swing on one foot can only be accompanied by stance in the opposite foot. The pairs of symbols for which this rule held, were considered good candidates and fed into the expert system.

A similar approach to context analysis was also explored in another article [71]. The difference to this previous work is that the context analysis described in **Paper I** was done automatically. Guerra-Filho and Aloimonos [30] also explored relationships between symbols by looking at the frequency with which

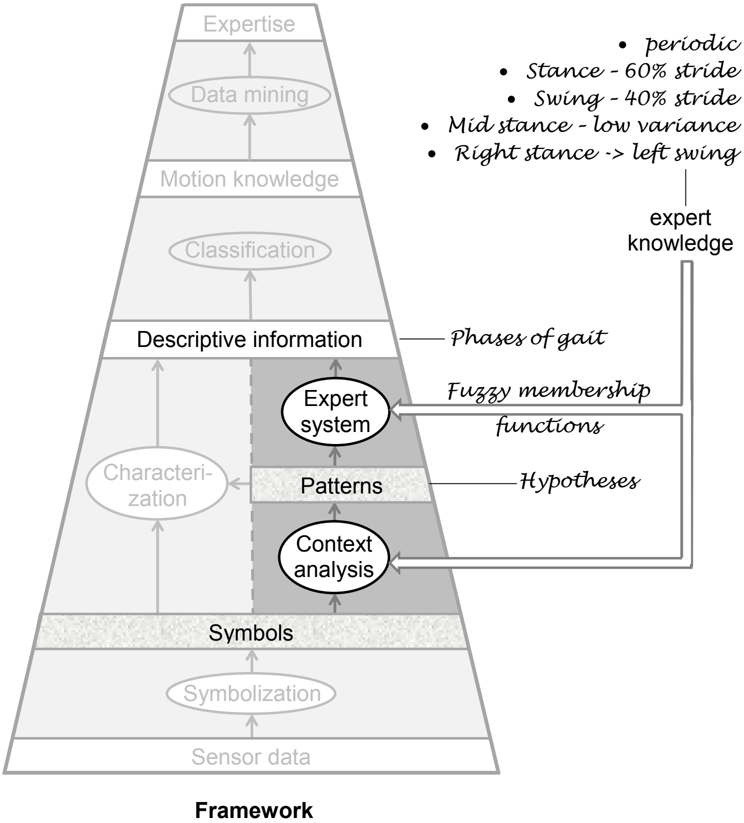

Figure 3.7: Context analysis and expert system processes within the framework. Context analysis uses expert knowledge to identify relevant symbols in the data. The expert system relates these symbols to gait events such as heel-strike and toe-off.

certain sequences appeared. These are only some examples of the many possible approaches to context analysis.

3.3.3 Expert System

The expert system is the second process along the right side of the framework pyramid in Figure 3.7. Although some expert knowledge can be used to guide context analysis, the expert system is the process that explicitly incorporates expert rules and helps link certain symbols or patterns to human concepts.

In **Paper I**, the knowledge reflected in the expert system was based on the following known facts about gait:

1. Approximately 60% of stride time corresponds to stance, the remaining 40% corespond to swing;

2. Toe-off events are reflected in the resultant acceleration as peaks;
3. Heel-strike events are reflected in the resultant acceleration as a valley and large variance;
4. The foot moves the least at mid-stance.

Each of these rules was coded as fuzzy membership functions that represented the degree to which the rule holds for each pair of potential HS and TO symbols [27]. Each possible combination of HS and TO symbols was evaluated with respect to all rules using the corresponding fuzzy membership functions. Results were multiplied to give an estimate of how well a particular combination of HS and TO symbols held for all rules. The combination with the highest value was chosen as the most adequate symbolic representation for HS and TO. It is worth noting that this same implementation successfully detected HS and TO on very distinct walking patterns; i.e. normal walk, slow walk and limping.

The expert system approach explored here is very simplistic. Commonly expert systems are a collection of if-then rules, *e.g.* [86]. Fuzzy logic can be used to incorporate uncertainty into the rules [62]. The reader is referred to the article by Liao [50] for an review of expert systems.

3.3.4 Characterization

Characterization is the process represented on the left side of the framework pyramid as illustrated in Figure 3.8. This is the general process of extracting movement information from the symbolic data. In gait analysis, characterization may involve aspects of coordination, stride-to-stride variability, gait stability, gait symmetry, among other measurements. In this thesis, gait symmetry and gait normality were investigated.

In **Papers II**, **IV**, and **V**, a measure of similarity between two symbolic strings was used. This similarity measure was based on histogram distributions of symbol periods or symbol transition periods. Symbol (transition) period histograms capture the frequency with which two consecutive occurrences of the same symbol take place x seconds apart, for many values of x. Symbol (transition) period distributions are different from signal distributions, which capture the probability of a particular symbol S occurring in the symbolic string.

This similarity measure was used to calculate gait symmetry and normality. Symmetry is the comparison between the movements of the right and left limbs. It is an important measure of gait and can be used to assess several physical and cognitive conditions, *e.g.* stroke [1] [64]; degenerative diseases [49]; prosthetics [80]; injury [4] among others. Normality, by contrast, is the comparison of a subject's gait against an external reference. And it is a general indicator of the general quality of gait of a patient [9] [74]. Very few methods have been developed for the quantitative assessment of normality, and even fewer using inertial sensors.

Paper II describes how the histogram similarity measure provided a measure of symmetry very sensitive to Parkinsonian symptoms, and more informative than traditional temporal methods. In **Paper IV**, both symmetry and normality indices were compared to 3D kinematic data. The same measures were then used to estimate quality of gait for hip-replacement patients and compared to quantitative and qualitative measures of patient recovery. This study is reported in **Paper V**. In **Papers IV and V**, the proposed measures performed very well with respect to the reference variables.

One of the advantages of this similarity measure is that the statistical nature of the histogram representation helps cope with step to step variability [15]. In addition, these symmetry and normality measures can be computed for any gait patterns, independently of identifying gait events or other spatio-temporal parameters. As a result, they can also be computed for upper limb movements during walking.

3.4 Summary

Quantitative gait analysis can be used as a measure of recovery after surgery. Quantitative patient outcome measures such as this are important for assessing the quality of service at health care institutions, as well as empowering patients to take control over their own health.

Many inertial sensor systems for gait analysis have been described in the literature, their main shortcomings can be summarized as follows.

1. Methods are tailored to specific applications and cannot be generalized easily;

2. Systems that use a small number of sensors typically only measure spatio-temporal information or general center of mass kinematics;

3. Expert knowledge is only incorporated implicitly as biomechanical models or *ad hoc* data processing;

4. Results are frequently incomprehensible for clinicians not experienced in gait analysis;

In order to address these issues, the proposed framework was implemented targeting a gait analysis application. The implementation explored the processes of symbolization, context analysis, expert system and characterization. Some of the results achieved with this implementation are summarized below.

1. The symbolic approach and the framework were successfully used to identify and detect the phases of gait;

2. Expert knowledge about gait was used to parse symbolic sensor data;

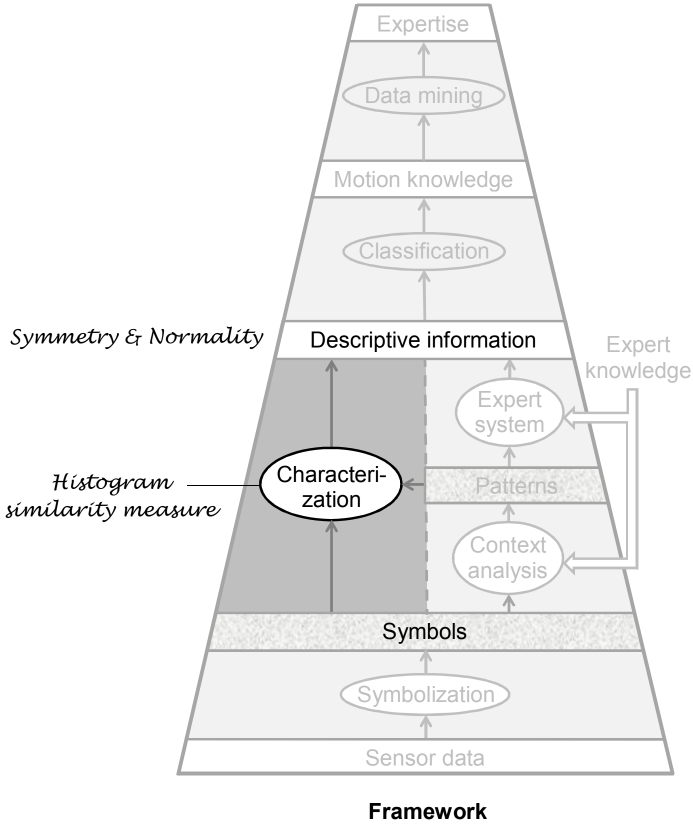

Figure 3.8: The characterization process within the framework. Characterization was achieved with a similarity measure based on histogram representations of symbol periods.

3. Walking pattern characterization was achieved independently of classification;
4. The proposed method was able to generalize the data analysis to different types of walk, namely normal walk, slow walk and limping;
5. A symbolic similarity measure was created to assess gait symmetry and gait normality;
6. The gait analysis system showed good results when evaluated against 3D kinematic data and when evaluated in a real clinical environment.

Chapter 4
Summary of Appended Papers

This section introduces the motivation, objectives and results of each individual paper, and how they relate to the overall objectives of this thesis.

4.1 Paper I - A symbol-based approach to gait analysis from acceleration signals: Identification and detection of gait events and a new measure of gait symmetry

Gait analysis can be used to help diagnose and assess the severity of neurological conditions such as Parkinson's disease [26], stroke [18] and cerebral palsy [14]. It can also help predict the risk of developing dementia and mild cognitive impairment in old age [11], or measure the recovery of a patient after trauma [4]. Unfortunately, gait analysis labs are rarely available in underprivileged areas; and when available, are not used in the treatment of most patients due to economic constraints [77]. In addition, in lab assessment cannot be used for continuous day to day monitoring. The creation of cheaper, wearable gait analysis systems using inertial sensors can help fill these gaps and enable the routine use of gait analysis for all patients.

The goal of **Paper I** was to propose a new method for processing inertial sensor data in order to improve the performance of wearable gait analysis systems. This method, based on the proposed framework, was used to detect the phases of gait and determine gait symmetry. Gait-phase results were compared to a peak-detection method, and symmetry results were compared to a traditional temporal symmetry measure and a cross correlation symmetry measure.

The proposed method was based on symbolization of the sensor signal followed by an analysis of the context and distribution of each symbol, see Appendix A for more details. The data used in this study was collected using two Shimmer® 3-axis accelerometer sensor nodes and a GaitRite pressure sensitive mat [56]. Six healthy subjects were equipped with one sensor node attached to each shin and asked to walk along the GaitRite in three different ways: normally, slowly, and with the right knee immobilized to simulate limping.

Results showed that the proposed method performed similarly to the reference method in detecting heel-strike and toe-off for normal and limp walk data. However, the proposed method considerably outperformed the peak-detection method for the slow walk data. This was probably due to the fact that acceleration peaks are not as prominent during slow walking. The proposed symmetry index outperformed the reference temporal symmetry measure and performed similarly to the cross-correlation method. This is probably explained by the fact that both the proposed symmetry measure and the cross-correlation method make use of the entire acceleration signal, instead of only temporal information.

Paper I contributed to this thesis by illustrating one possible implementation of the framework applied to gait analysis. It showed how expert knowledge can be used to parse and process the symbolic data, and that the proposed symbolic approach is potentially more informative than previous methods.

4.2 Paper II - A new measure of movement symmetry in early Parkinson's Disease patients using symbolic processing of inertial sensors data

There is evidence that movement asymmetry is commonly observed in conjunction with a decline in health status [87]. Parkinson's Disease (PD) patients, in particular, may exhibit very asymmetrical gait [8], and asymmetrical hand movements [39]. Although many symmetry measures have been suggested in the literature, there is still no accepted standard, which suggests that each application may require a different optimal measure.

The objective of **Paper II** was to introduce, evaluate and benchmark a new measure of movement symmetry based on inertial sensor data, appropriate for early-to-mid-stage PD patients. The proposed method was compared to six other symmetry measures.

The proposed symmetry measure was based on symbolization of the sensor data and description of the signal in terms of period histograms, see Appendix B for more detailed information. The data used in this study was acquired using a portable data-logger (Physilog ™ from BioAGM, Switzerland) with four inertial sensors. Eleven subjects with idiopathic PD and 15 control subjects wore a 1-axis gyroscope attached to the anterior shank of each limb and a 2-axis gyroscope attached to the dorsum of each wrist along pitch and roll axes. Subjects walked up and down a 30-meter hallway for two minutes. All seven symmetry measures were calculated for upper and lower limbs.

Upper limb symmetry results were more useful than lower limb results for differentiating controls from patients. The proposed symmetry measure presented higher sensitivity and specificity than the other six methods. The proposed method also showed better test-retest reliability, 55% better than second best method.

Paper II showed that a symbolic representation of the data can potentially improve the analysis of movement symmetry for early PD patients. This illustrates the usefulness of the proposed symmetry measure for clinical applications.

4.3 Paper III - Symbolization of time-series: An evaluation of SAX, Persist, and ACA

Symbolic time-series analysis has been successfully used in many different application areas to identify temporal patterns in experimental data. It can reduce sensitivity to noise and greatly improve computational efficiency [19]. Symbolization of time-series also enables the use of techniques developed for symbolic data, *e.g.* data mining in databases [12], data mining on DNA sequences [48], text mining [22], knowledge representation and reasoning [46], and computational linguistics [61]. An unavoidable part of the symbolization process is segmentation. Time-series segmentation can be described in two domains: the amplitude or the temporal domain. We refer to the former as quantization, and to the latter as temporal segmentation.

The goal of **Paper III** was to determine if symbolization methods can be chosen based on *a priori* signal characteristics; and test the hypothesis that temporal segmentation is more appropriate for symbolizing periodic signals, whereas quantization is better for segmenting random signals.

Two quantization methods, SAX and PERSIST, and one temporal segmentation method, ACA, were investigated. These methods were used to symbolize 47 different unidimensional signals extracted from several public databases. Signals were divided into four groups according to a measure of periodicity based on auto-correlation. The symbolization methods were evaluated based on information loss and compression factor for each of the four groups.

ACA considerably outperformed the quantization methods on one highly periodic signal. However, results were less consistent for the remaining signals in the same group. Similarly, SAX outperformed the other two methods on some non-periodic signals, but not on all signals in the same group. As a result, the hypothesis was not confirmed statistically.

Paper III compared three different approaches to symbolization. It was evident from this study that the comparison of temporal segmentation and quantization methods for symbolization is not trivial. Symbolization is normally accompanied by further analysis, and the evaluation of symbolization methods in isolation might not reflect their behavior within the framework. Furthermore, other signal characteristics and other performance variables may be more successful in unveiling the characteristics of symbolization methods.

4.4 Paper IV - A wearable gait analysis system using inertial sensors Part I: Evaluation of measures of gait symmetry and normality against kinematic data

Gait symmetry and normality are important measures that can aid the clinical assessment of patients. Symmetry can be used to assess several physical and cognitive conditions, *e.g.* stroke [1] [64]; degenerative diseases [49]; prosthetics [80]; injury [4] among others. Whereas, normality is a general indicator of the general quality of gait of a patient [9] [74]. Although a large number of symmetry measures have been proposed, very few methods have been developed for the quantitative assessment of gait normality.

The goal of **Paper IV** was to introduce a new measure of gait normality using inertial sensors; and to evaluate this measure of normality, and a previously proposed measure of symmetry, against reference measurements derived from 3D kinematic data.

Both normality and symmetry measures were calculated by symbolizing the sensor data and creating symbol period histograms. Symmetry is a comparison of the histograms from right and left sides, and normality is a comparison of the subject's histogram to a reference histogram. The data used in this study was acquired using 3 Shimmer® sensor nodes, each containing a 3-axis accelerometer and a 3-axis gyroscope; and a Qualisys 3D mocap system. Eighteen healthy subjects were equipped with one sensor node on each shin, and one sensor on the waist below the navel. Subjects were simultaneously recorded with both systems while walking along a straight line in 3 different ways: normally, slowly and limping. The mocap external reference data consisted of a previously acquired set of 34 randomly selected adult subjects presenting no known pathologies. The inertial sensor reference data set was a small subset of the subjects presenting most normal walk based on the kinematic data.

Results showed that the proposed methods were well correlated to kinematic measurements. The best normality correlation was obtained between the proposed normality measure, using the waist sensor data, and the kinematic normality measure using all lower limb joints combined. The corresponding Spearman's rank correlation coefficient was $r=0.81$, $p<0.0001$. The best symmetry correlation was obtained between the proposed symmetry measure, using shin sensors, and the kinematic symmetry measure considering all lower limb joints. This Spearman's rank correlation coefficient was $r=0.84$, $p>0.0001$.

The main contributions of **Paper IV** were the introduction of a measure of gait normality using inertial sensors, and the validation of the proposed normality and symmetry measures against 3D kinematic data.

4.5 Paper V - A wearable gait analysis system using inertial sensors Part II: Evaluation in a clinical setting

Gait analysis is a tool that can aid the assessment of several conditions. Despite many positive results, gait analysis is not routinely used in the clinical setting. Several factors contribute to the low adoption of gait analysis as a clinical tool, such as economic constraints [77], and difficulty in undertaking the analysis and interpreting results. In addition, assessments are long and results are not instantaneous. Wearable gait analysis systems based on inertial sensors can help popularize the use of gait analysis. Quantitative measures of quality of gait, in particular, may provide quick and intuitive outcome measures for clinical assessment. However, much work is still needed in order to validate such systems and show their usefulness.

The goal of **Paper V** was to investigate the validity and usefulness of previously introduced symmetry and normality measures, using inertial sensors, in a clinical setting. These quantitative measures of symmetry and normality were compared to traditional qualitative and quantitative patient outcomes after hip-replacement surgery, in order to determine if these measures were adequate for assessing the recovery of patients.

The data used in this study was acquired using 3 Shimmer® sensor nodes, each containing a 3-axis accelerometer and a 3-axis gyroscope. Subjects were equipped with one sensor node on each shin, and one on the waist below the navel. Eleven hip-replacement patients were measured with the sensor nodes while walking along a 10-meter walkway. The time to complete the walkway and the number of steps taken were also recorded. This procedure was repeated on the day of discharge from the hospital and approximately three months later. Patients were also asked to answer (EQ-5D) questionnaires about mobility, selfcare, daily activities, pain or discomfort, and anxiety or depression. The proposed measures of symmetry and normality were compared to walking speed, step length, length of stay at the hospital, as well as questionnaire results.

The questionnaire results showed that the largest differences before and after surgery were related to pain or discomfort, mobility, and daily activities. Normality values three months after surgery were better than at discharge for all patients. Normality results also correlated well with step length and average walking speed, two indicators of better walking ability. Normality measures correlated particularly well with the daily activity section of the questionnaire. That is, patients who reported being able to go about daily activities without any problems had better normality measures than those that reported problems. Another interesting result was that the number of days spent at the hospital after surgery correlated well with improvement in normality. That is, patients who had the largest improvement in normality from baseline to follow-up, had spent less time at the hospital.

Paper V showed the potential of the normality measure to contribute to everyday assessment in a clinical environment. Measures were easy to understand and correlated well with intuitive assessments of improvement. This shows that the framework can contribute to the development of systems to be used in clinical environments.

Chapter 5
Conclusions

This chapter highlights the main aspects of this work. First, research questions, framework, and main results are summarized. Then, relevant issues related to the framework and its implementation are discussed, and future research directions are highlighted. Finally, some general conclusions are drawn.

5.1 Summary

Research Questions

Motion analysis system should address both classification and characterization of movements. This work considered new data processing and analysis methods for inertial sensor data as means of improving wearable motion analysis systems. The main research gaps related to motion analysis were investigated from two different perspectives, motion analysis systems in general, chapter 2; and gait analysis systems in particular, chapter 3.

In order to address the identified research gaps, this thesis focused on the following general motion analysis research questions: How to organize different approaches to movement analysis, and define characterization and classification as independent problems? How can symbolization be used as an intermediate representation for motion data, which facilitates movement characterization? How can expert knowledge be used to parse sensor data and facilitate its interpretation?

The following gait specific research questions were also investigated: How can symbolization improve the characterization of different gait patterns? Can signal symbolization and the addition of expert knowledge help generalize gait analysis to different walking patterns?

Framework

In order to address the afore mentioned research questions, a framework was introduced in section 2.3, which organized motion analysis methods as sequences of tasks at different levels of abstraction. This allowed the definition of characterization and classification of movements as independent problems. In addition, the framework took advantage of expert knowledge in order to parse sensor data and extract relevant information. The inclusion of expert knowledge also facilitated the interface between sensor data analysis and human experts.

An important part of the framework was the symbolization of inertial sensor data. This approach simplified the data representation by mapping the continuous signal to a limited set of symbols. This symbolic representation gave rise, in particular, to a similarity measure, which was used for movement characterization. In addition, the symbolic representation facilitated the correspondence between expert knowledge and particular events recorded in the sensor data.

Implementation and Results

A gait analysis application was chosen as a test bed for the framework. The framework tasks related to symbolization, context analysis, expert knowledge and characterization were implemented as part of a wearable gait analysis system. This implementation was described in section 3.3.

In particular, a combination of symbolization, context analysis and expert system was used to identify the phases of gait from accelerometer data, as explained in **Paper I**. The proposed method was compared to reference measurements obtained with a pressure sensitive mat, and to a peak-detection method described in the literature. Results showed that the proposed method was as accurate as the peak-detection method, except for the slow walk data set, on which the proposed method performed considerably better.

Based on symbolized inertial sensor data, a measure of signal similarity was created. This measure was used to characterize movement symmetry in early-to-mid-stage Parkinson's Disease patients in **Paper II**. The proposed symmetry measure was compared to four other indices based on discrete temporal variables, and two methods based on continuous signals. The symbol-based index considerably outperformed the other methods. The proposed index presented high sensitivity and specificity, and excellent test-retest reliability, almost double that of the second best method.

The symbol-based similarity measure was also used to create a measure of gait normality in **Paper IV**. This was the first normality measure based on inertial sensor data described in the literature. Both symmetry and normality measures were compared to state-of-the art kinematic measurements. Results showed that the proposed indices were highly correlated to the kinematic reference. Moreover, these indices were compared to patient-reported outcomes and other measures of improvement obtained from a group of hip-replacement patients in **Paper V**. Results showed that the proposed symbol-based indices provided an assessment of quality of gait and level of recovery for this group of patients.

5.2 Discussion and Future Work

Framework

The proposed framework is most vulnerable to two processes in particular: symbolization and context analysis. As explained in section 3.3, symbolization is the process that transforms continuous sensor data into strings of symbols. Context analysis deals with understanding and describing the relationships between symbols or sequences of symbols.

Choosing an appropriate symbolization technique is an important and difficult task. Quantization and temporal segmentation aspects were explored in **Paper III**. Nonetheless, the comparison of different symbolization methods is not straightforward. In order to simplify the comparison in **Paper III**, the symbolization process was isolated from the rest of the framework, and methods were judged based on their signal reconstruction properties. However, the reconstruction of the signal is not the intended purpose of the framework. The evaluation of different methods could have been very different if symbolization had been considered as pre-processing, and results had been compared after classification or characterization. The drawback of considering symbolization within the framework is that there are numerous possible combinations of symbolization and analysis methods, which cannot be comprehensively addressed. For that reason, most works symbolize signals based on intuition and expert knowledge about the signal and/or movement under observation. Methodologies for the evaluation of symbolization approaches should be further investigated. Future work may include the evaluation of symbolization techniques combined with simple classification methods.

The context analysis reported in this thesis explored only very simple relationships between symbols, guided by expert knowledge. More complex and automated context analysis approaches have been described in the literature. Guerra-Filho and Aloimonos [30] worked with symbolized sequences of joint angle kinematics obtained from 3D mocap data. Rules were created to describe sequences of symbols based on how frequently certain pairs of symbols appeared. The most common pair was represented by *rule 1*, the second most common pair by *rule 2*, and so on. Rules could also be formed by grouping symbols and rules. In this way, a hierarchical structure of rules was created to represent a symbolic string. Similarly, rules were derived to express movements in terms of several concurrent joint angle sequences.

Another work, by Mörchen and Ultsch [59], investigated the temporal relations between different sources of concurrent symbolic signals in order to create linguistic descriptions of an activity. Temporal relations between symbols were expressed as interval relations such as "symbol A overlaps symbol B" or "symbol A follows symbol B". Groups of relations can be refined to express meta rules or general descriptions that can be easily understood by human experts if the meaning of each symbol is known. This method is very general and can be used to describe combinations of different signals in a very intuitive way. Such linguistic descriptions can easily be incorporated into the proposed framework.

Another common way of representing symbol sequences is using Hidden Markov Models (HMM). Which can model an observable sequence (sensor data) and estimate the most probable underlying states (movements) that generated such sequence. HMMs may be used to express relationships between different symbols as well as represent typical symbol sequences. Many works have used HMM for classification, but there is also potential for their use in the characterization of activities. Metrics have been developed for measuring distances or similarities between two HMMs [7]. These metrics may be used to quantify differences between performances of a certain activity. One of the challenges involved in using HMM is choosing an appropriate representation of states. States are typically represented by statistics of features extracted from the sensor data [82], [47], but they may also be manually constructed combinations of features [36].

Implementation

The characterization of gait using inertial sensors may involve many different types of measurements and variables, from kinematic and spatio-temporal domains. This thesis focused on new measures of gait symmetry and normality. These characterization variables were based on a measure of similarity between two symbolic strings, which took into account mostly temporal characteristics. Other measures of symmetry and normality can be derived from kinematic and spatial variables such as stride length and joint angles, *e.g.* [17] [74]. However, the acquisition of such spatial and kinematic variables requires the numerical integration of accelerometer and gyroscope signals. A process susceptible to accumulated measurement errors, due to the fact that inertial sensors are commonly affected by bias drift [52]. In addition, Kalman filter methods, typically used to combine acceleration and gyroscope data into spatial information, are also sensitive to drift errors that must be compensated for [68] [65]. Therefore, mostly temporal variables were considered in this work, in order to minimize the effect of drift errors and facilitate the manipulation of the data.

Throughout the five appended papers described in this thesis, different sensor configurations were used depending on the resources available at the time.

Papers IV and **V**, in particular, made use of both 3-axis accelerometers and 3-axis gyroscopes. Sensors nodes were attached to the subjects' shanks and waist as illustrated in Figures 3.2 and 3.3 respectively. The acceleration and gyroscope data were processed independently and underwent the same analysis. Results showed that, when using the symbolic approach, the accelerometer sensors placed on the waist provided normality measures that correlated better with the kinematic reference data; whereas the shank gyroscope sensors provided better symmetry measures. Further investigations are needed to determine why this was the case, and if the preferred configurations would be the same when comparing to other reference measurements.

In this thesis, shanks, wrists and waist were the preferred sensor positions. However, other positions such as arms, thighs, chest and lower back have been reported in other studies. Some studies have characterized gait patterns using sensors placed on the lower back [2] [57], based on the assumption that this location is closer to the body's center of gravity. Recently, Atallah *et al.* [5] investigated the effects of sensor position and feature selection on activity classification tasks using accelerometers. Their study concluded that optimal sensor positions depend on the activities being performed by the subject. Other important factors to consider, especially if the system is designed for long and continuous use, are how comfortable it is to wear and how easy it is to put on. Frequently, accuracy must be compromised for ease of use and comfort, due to a reduction in number of sensors. The optimal system configuration is, therefore, difficult to evaluate. It depends not only on the accuracy of the system but also on other practical aspects.

Applications

Another interesting characterization measurement is gait variability, for it "offers a complementary way of quantifying locomotion and its changes with aging and disease, as well as a means of monitoring the effects of therapeutic interventions and rehabilitation" [34]. Gait variability is a measure of how gait parameters change from stride to stride. It is normally defined as the within-subject standard deviation or coefficient variation of gait parameters over several strides. Studies have shown that changes in stride time are more random in elderly and Huntington's Disease patients compared to young controls [35]. Stride time and swing time variability also increases in Parkinson's Disease patients [26]. This variability is significantly linked to falls and becomes worse as the disease progresses [33]. Measures of gait symmetry, normality and variability together span all dimensions of movement similarity: how one side compares to the other side; how both sides compare to an external reference; and how movements change over short periods of time. Therefore, future developments of the proposed gait analysis system should investigate measures of stride-to-stride variability.

The framework should also be validated for activities other than walking. Before tackling whole-body movements, it would be interesting to investigate the use of the framework for identifying and characterizing sign language or other well defined hand gestures. After that, a combination of coordinated upper body and lower body movements such as dancing or swimming would be interesting to investigate.

5.3 Conclusion

Many health-related monitoring applications may profit from motion analysis systems composed of inertial sensors. Inertial sensors are cheap, small, and can be conveniently embedded into garments such as watches, shoes and mobile phones. However, additional research efforts are required in order to process inertial sensor data for movement characterization in particular.

This thesis introduced a framework for motion analysis based on different levels of abstraction. The framework defined classification and characterization as independent problems, and focused on creating a data representation that facilitated movement characterization. This framework can not only be used to structure previous works, but it also serves as a road-map to the development of new motion analysis systems.

The foundation of the framework is the symbolization of sensor signals, and many such approaches were investigated here. Although the comparison of these symbolization methods was far from trivial, and the choice of optimal method is still unclear, the different implementations of the framework achieved excellent results. A similarity measure was created based on the symbolized signal, and used to characterize symmetry and normality. And expert knowledge was used to parse the symbolic data and link certain data events to human concepts.

Movement characterization was targeted in this thesis because the ability to quantitatively measure differences in the performance of activities over time, or before and after treatment, is essential to health-related monitoring applications. The proposed measures of symmetry and normality are clear examples of the importance of movement characterization, and in particular, gait characterization. Such systems, capable of quantifying quality of movement, may one day revolutionize routine clinical practices both within and outside health-care facilities.

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