AUTOMATIC HUMAN MOVEMENT ASSESSMENT WITH SWITCHING LINEAR DYNAMIC SYSTEM: MOTION SEGMENTATION AND MOTOR PERFORMANCE

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TESE DE DOUTORADO EM ENGENHARIA DE SISTEMAS ELETRÔNICOS E DE AUTOMAÇÃO

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"Most advances in science come when a person for one reason or another is forced to change fields. Viewing a new field with fresh eyes, and bringing prior knowledge, results in creativity- Peter Borden

"It was the best of times, it was the worst of times,..., it was the spring of hope, it was the winter of despair"-Charles Dickens. It would have been impossible to complete this thesis without the support of my advisor, my co-advisor, colleagues, family and friends. Motivation comes easy when everything is going as planned, but it requires a helping hand when all seems to be sinking. I am thankful to everyone who gave me any encouragement, even just one kind word at the right moment.

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Outside the lab, I owe special thanks to my family and Raquel for their unconditional support and comprehension. Thanks for your kindness and for helping me maintain my sanity.

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RESUMO

AUTOMATIC HUMAN MOVEMENT ASSESSMENT WITH SWITCHING LINEAR DYNAMIC SYSTEM: MOTION SEGMENTATION AND MOTOR PERFORMANCE

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Brasília, 7 de novembro de 2016

Palavras chave: Análise Automática do Movimento Humano, Avaliação do Movimento Humano, Sistema Linear Dinâmico Chaveado.

Desenvolvimentos recentes na tecnologia de sensores portáteis estão trazendo dispositivos de medição de movimento humano para atividades cotidianas. Esses sensores fornecem aos usuários finais e profissionais de biomecânica uma quantidade de dados sem precedentes. Além disso, eles proporcionam o desenvolvimento de novas tecnologias em próteses inteligentes e sistemas de interação homem-máquina. No entanto, há uma falta de técnicas para extrair automaticamente as medições indiretas - tais como duração do movimento, amplitude ou coordenação motora - a partir desses dados. Medidas indiretas são necessárias para o reconhecimento, avaliação e análise do movimento humano, e são geralmente extraídas manualmente por meio de inspeção visual por um profissional de biomecânica. Esta tese propõe um novo método para a avaliação automática de movimentos humanos que executa segmentação e extração de parâmetros de desempenho motor (isto é, medições indiretas) em séries temporais de medições de uma seqüência de movimentos humanos. Utilizamos os elementos de um modelo de Sistema Dinâmico Linear Chaveado como blocos de construção para traduzir definições e procedimentos formais da análise tradicional do movimento humano. Nossa abordagem fornece um método para os usuários sem experiência em processamento de sinal para criar modelos para movimentos usando conjunto de dados rotulado e mais tarde empregá-lo para a avaliação automática. Validamos nossa estrutura de testes preliminares envolvendo seis sujeitos adultos saudáveis que executaram movimentos comuns em testes funcionais e sessões de exercícios de reabilitação, como sentar-se-levantar e elevação lateral dos braços, e cinco sujeitos idosos, dois com mobilidade limitada, que executaram o movimento de levantar-se da posição sentada. O método proposto foi aplicado em sequências de movimento aleatório para o duplo propósito de segmentação de movimento (precisão de 72-100%) e avaliação de desempenho motor (erro médio de 0-12%).

ABSTRACT

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Keywords: Automatic Human Movement Analysis, Human Movement Assessment, Switching Linear Dynamic Systems.

Recent developments in portable sensor technology are bringing human movement measurement devices to everyday activities. These sensors provide end users and biomechanists with unprecedented amount of data. Besides, they allow novel technologies in intelligent prosthesis and human-machine interaction systems to emerge. However, there is a lack of techniques to automatically extract indirect measurements - such as movement duration, amplitude or motor coordination - from these data. Indirect measures are necessary for recognition, assessment and analysis of human movement, and are usually extracted manually through visual inspection by a biomechanist. This thesis proposes a novel framework for automatic human movement assessment that executes segmentation and motor performance parameter extraction (i.e. indirect measurements) in time-series of measurements from a sequence of human movements. We use the elements of a Switching Linear Dynamic System model as building blocks to translate formal definitions and procedures from traditional human movement analysis. Our approach provides a method for users with no expertise in signal processing to create models for movements using labeled dataset and later employ it for automatic assessment. We validated our framework on preliminary tests involving six healthy adult subjects that executed common movements in functional tests and rehabilitation exercise sessions, such as sit-to-stand and lateral elevation of the arms, and five elderly subjects, two of which with limited mobility, that executed the sit- to-stand movement. The proposed method worked on random motion sequences for the dual purpose of movement segmentation (accuracy of 72-100%) and motor performance assessment (mean error of 0-12%).

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Notation and Abbreviations

MOCAP - Motion Capture System

IMU - Inertial Measurement Unit

DTW - Dynamic Time Warping

TUG - Timmed Up and Go (test)

HMM - Hidden Markov Model

ZVC - Zero Velocity Crossing

LDS - Linear Dynamic Model

DBN - Dynamic Bayesian Network

FB - Forwards-Backwards

RTS - Rauch-Tung-Striebel

SLDS - Switching Linear Dynamic System

ABI - Acquired Brain Injury

VE - Virtual Environment

FSM - Finite State Machine

FP - False Positive

FN - False Negative

MT - Movement Type

CPG - Central Pattern Generator

GUI - Graphic User Interface

List of Symbols

i.i.d. - Independent with identical probability distribution

e - event

c - component

p - phase

m - movement

s - switching variable (scalar SLDS)

$\mathbb{S}$ - set of symbols for s

$\mathcal{S}$ - family of sets of $\mathbb{S}$

σ- switching variable (multidimensional SLDS)

$\mathbb{D}$ - set of symbols for σ

$\mathcal{D}$ - family of sets of $\mathbb{D}$

x - hidden state in state-space model (scalar)

$\boldsymbol{x}$ - hidden state in state-space model (multidimensional)

A - state transition matrix (state-space model)

$\boldsymbol{r}$ - hidden state noise

Q - covariance of hidden state noise

y - observed measurement in state-space model (scalar)

$\boldsymbol{y}$ - observed measurement in state-space model (multidimensional)

C - observation matrix state-space model

w - measurement noise

Π - state transition matrix (HMM model)

α- forward operator (forwards-backwards algorithm)

β - backwards operator (forwards-backwards algorithm)

γ- combined operator (forwards-backwards algorithm)

v - constant velocity parameter

Σ- variance

J - smoother gain matrix RTS

$\mathcal{J}$ - set of joints/kinematic variables j

φ - mapping function $\mathbb{S} \to \mathbb{D}$

$\mathcal{P}$ - set of ordered pairs with movement period

$\mathcal{T}$ - set of movement types τ

$\mathbb{E}$ - set of symbols s associated with end of movement

$\mathcal{C}$ - cost function in the SLDS-Viterbi

T - period or time-series length

L - lag in fixed lag smoother

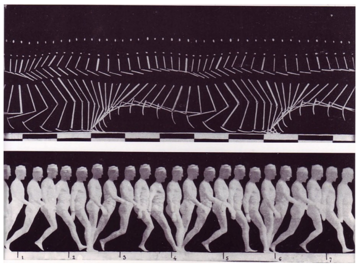
1 INTRODUCTION

Human movement science is on the verge of a revolution. Portable, low-cost sensors are quickly making their way in everyday activities, providing measurements of human motion which were previously reserved to cumbersome laboratory equipments and procedures. The amount and availability of quantitative data on human movement will directly impact in many areas such as: sports, rehabilitation and human-machine interaction.

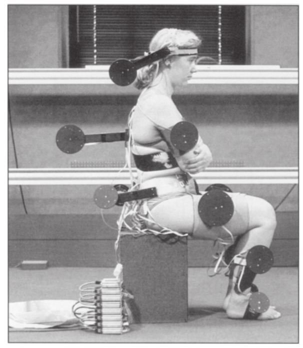
Human movement science, specifically biomechanics, has evolved alongside measurement devices, as illustrated in Figure1.1. Starting from the early works of photographic studies of Etienne-Jules Marey and Eadweard Muybridge in the 1880s, where sequences of photographs enabled qualitative understanding, description and assessment of human movements [4], passing on to the development of optical and wearable sensors in the 1980s and 1990s, which enabled quantitative measurements and therefore objective description, assessment and quantitative analysis [2]. But cumbersome setups limited the measurement of human movement to research settings. Today, the widespread of portable low-cost sensors have the potential to provide biomechanist and end users an unprecedented amount of quantitative data of human movement [5, 6]. The interpretation and usage of these measurements are still an emerging field of study. Nonetheless, the deep understanding and advance usage of these measurements are the cornerstone to unfold new techniques and procedures for human movement assessment.

It is a consent that feedback on movement execution from a qualified professional is effective in performance improvement [7]. Moreover, during either in sports or rehabilitation sessions, incorrect execution of movements may lead to injuries or, at least, make the training session ineffective. Kinesiologists observe key features in movement execution and they rely on their knowledge to assess the quality of the execution of the movement. Based on this assessment and their experience they provide feedback to the subject with the goal of improving performance. Furthermore, the trainer is responsible for monitoring the evolution of the subject over time - based either on qualitative observations or quantitative measurements - to inspect the effectiveness of training.

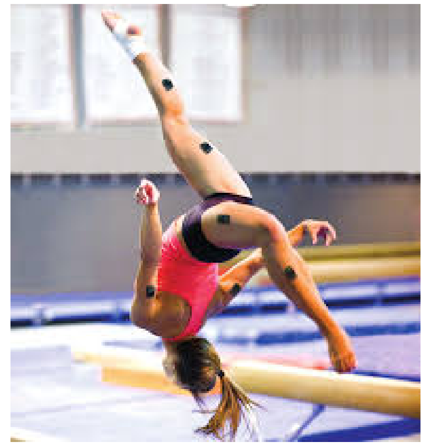
Expertise in biomechanics is nowadays built on quantitative data and objective descriptions to gain scientific knowledge of how and why a movement is executed in a certain way [4]. In everyday practice, however, the kinesiologist will look at the movement executed by a subject and mentally execute a few tasks in order to assess the movement. First, even in a controlled environment, a movement is rarely executed alone, rather it is often part of a sequence of movements. The kinesiologist must mentally segment the sequence of move-



(a) Sequence of photographs from Etienne-Jules Marey circa 1880s



(b) Laboratory setup for sit-to-stand analysis from 1990s [2]



(c) Gymnast using portable sensors 2010s[3]

Figure 1.1: Evolution of human movement measurement devices.

ments to focus on the movement to be assessed. Second, inherent to segmentation, he must recognize which movement was executed. Next, once he is observing the desired movement, he will recognize critical attributes to evaluate the movement, for example: has a gymnast raised his arm high enough at the takeoff of a somersault? Has a patient leaned his trunk excessively forward during a sit to stand movement? Finally, the kinesiologist must monitor these critical attributes over many executions and training session to check for improvement. Portable sensors enhance observation, but assessment and monitoring are still carried out by the kinesiologist [8, 5].

The areas of augmented biofeedback and, more recently, telerehabilitation have gained much attention in the past few years because the literature shows that intensive practice schedules benefit acquisition and recovery and motor function [9, 10]. However, intensive practice schedules should be associated with supervised training for assessment, feedback and medium to long term monitoring, with the risk of running the session ineffective or event lead to injury. Professionally intensive supervised motor training sessions is not a realistic outlook in today's scenario. The number of athletes or patients greatly outnumbers the number of qualified professionals. As a result, restricted time is spent in supervised training scenarios. Motion tracking combined with automatic assessment technology can assess and provide feedback to the user to correct the movement execution and monitor the progress over time. The advent of this technology can decrease the workload of trainers and offer the possibility of supervised personalized training sessions for a larger audience as well as releasing trainers to perform additional higher level evaluations and procedures.

Another area with potential application of automatic human movement assessment is the development of intelligent prosthesis. These electro-mechanical devices interpret the human movement and act to restore impaired functions of the body. Although some attention has been given to automatic human movement segmentation and assessment they are usually simple computational solutions developed specifically for each device and function restored [11].

Furthermore, the techniques presented in this thesis could also be applied to human-machine interactions. As more appliances are equipped with motion sensors, the area of multimodal interaction, i.e. interacting with machines through touch, speech and gesture, become more tangible. Multimodal interaction offers not only comfort and flexibility, but may open possibilities of human-machine interactions for individuals with impairments [12].

To summarize, much attention has been given to evidence-based objective movement description, motor control learning with augmented feedback and telerehabilitation. Likewise much attention has been given to portable and low-cost sensor technology for human movement measurements. In contrast, little attention has been given to automatic movement assessment. The reason is that automatizing tasks seemly easy for humans - such as recognizing movements, determining the start and end of a movement and observe key features of the movement to judge its quality - requires from one side deep understanding of human nature of the tasks to be automatized and from another side advanced mathematical models and complex machine learning techniques. In this thesis we automatize the process of segmentation, movement type recognition, and assessment.

The main contributions from this thesis can be summarized as:

1. **Unified mathematical approach for automatic segmentation, movement type recognition and motor performance parameters extraction:** different from previous works in the literature, we use the same mathematical modeling and estimation procedures to solve the required tasks for automatization of human assessment. This simplifies software implementation, model parametrization and application of the method to any type of movement described by kinematic parameters.

2. **Parametrization procedures that require no background in signal processing:** our proposed method uses manually labeled data sets to automatically parametrize the mathematical models. Therefore professionals with no background in signal processing may directly use our proposed framework without the need to understand the underlying mathematics.

3. **Implementation and validation on diverse experiments:** we implemented our method and tested under different conditions with varied population to showcase performance

and applicability.

This manuscript is organized as follows: Chapter 2 provides the reader with the necessary theoretical background from both human movement analysis and stochastic modeling and estimation to understand the framework proposed in this thesis. Next, in Chapter 3, the recent developments in automatic human movement segmentation and assessment are presented. Then, in Chapter 4, the proposed framework for using switching linear dynamic system modeling for automatic human movement segmentation and assessment is presented. Following, four case studies are presented to showcase the features of the proposed framework. In Chapter 5 a movement cycle diagram is obtained with the proposed framework and compared with an heuristics approach. In Chapter 6 a multivariate case is used to accomplish segmentation, movement type recognition and motor performance parameters extraction, the processing is done offline. In Chapter 7 an online variation of the proposed framework is used for online segmentation and motor performance parameters extraction. To conclude the case studies, in Chapter 8 the framework is used to extract motor performance parameters from a database collected from elderly subjects. Finally overall conclusions and outlooks are presented in Chapter 9.

2 THEORETICAL BACKGROUND

2.1 IMPORTANCE OF HUMAN MOVEMENT ANALYSIS

Kinesiology is the science of human movement. Biomechanics is a sub-discipline of kinesiology that involves precise description of human movements and the study of the mechanics that causes the movement [7].

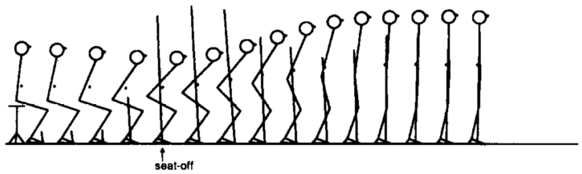
The study of biomechanics is relevant to professional practice in many kinesiology professions. In everyday practice an athletic trainer or rehabilitation therapist rely on measurements or visual observations to analyze the movement execution. They count on their experience (on biomechanics) to pay attention to certain aspects of the movement at particular moments. Based on these observations and background knowledge the coach or therapist may infer the causes of this poor execution due to lack of technique or impairment.

The role of most kinesiology professionals is to prescribe technique changes and give instructions that allow a person to improve performance. Either for athletes to advance their technique or patient to enhance or restore movement capability.

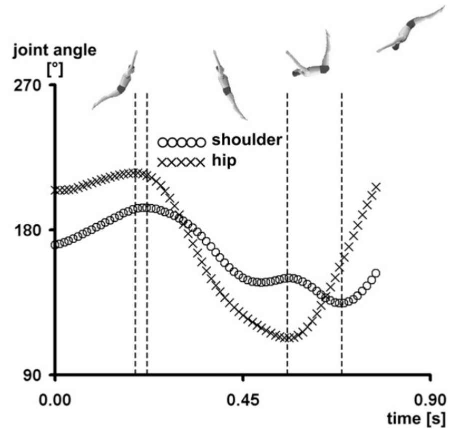
The reason of any assessment is to enable a positive decision about a physical movement. An athletic trainer might check if a variation of a technique will minimize the mechanical energy required for a certain movement. An orthopedic surgeon may wish to observe improvements in knee strength of a patient a month after surgery. A basic researcher may wish to interpret the motor changes due to controlled perturbation to verify or negate different neural control theories [4].

Human movement assessment falls on a continuum between qualitative and quantitative. Quantitative analysis requires the measurements of biomechanics variables and usually requires electronic sensors and computer processing. Even short movements may result in thousands of samples of data to be collected, scaled and numerically processed. On the contrary, qualitative analysis is defined by [7] as: "systematic observation and introspective judgment of the quality of human movement for the purpose of providing the most appropriate intervention to improve performance".

Numerical measurement systems enable precise observations of what may escape the eyes. The advantages of quantitative over qualitative assessment are: accuracy, consistency and precision. Besides, it provides a mean for objective comparison. Moreover, the use of numerical measurement systems allows the establishment of baseline values for variables associated to different movements.



(a) Stick figure of the sit to stand movement [15].



(b) Plot of time-series of angle joint in a gymnastics movement [16].

Figure 2.1: Descriptions of movements.

These advantages comes at cost and complexity, as a result most quantitative biomechanics analysis is performed in research settings. However, in recent years there has been an increase in low-cost, commercially available and easy to use devices to measure biomechanics variables [13, 14, 7].

As strongly emphasize by [4], "the scientific approach to biomechanics has been characterized by a fair amount of confusion". It is common to find misused terms in the literature when reporting studies. Descriptions of human movement are often referred to assessment and studies containing only measurements have been falsely passed on as analysis, to cite two recurring examples. Consequently, these terms must be clearly defined.

Measurements are the quantities provided by the sensors (although post-processing may be required) for each biomechanics variable.

Descriptions are forms of representing measurements to facilitate assessment. They can take the graphical form such as: time-series plots, movement cycle diagrams or stick-diagrams such as depicted in Figure 9.1. Or they can be a mathematical formula that results in an outcome measure such as: gait velocity or maximum heigh of a jump. Throughout this thesis outcome measures will be referred to as motor performance parameters.

Assessment is the act of evaluating, i.e. estimating or judging the value of a variable.

To monitor means to perceive changes over time. A coach may monitor the improvement of technique from an athlete, while a therapist may monitor the rehabilitation of a patient. Monitoring, however, does not inform why improvement (or lack of) happened, it merely documents changes over time.

To analyze is to examine the movement carefully and in detail so as to identify causes, key factors and possible outcomes.

Baseline valuesand descriptions are important tools for assessment and analysis of human movements in sports and healthcare.

In sports, for example, [16] investigates the ideal timing and angle variability in a complex gymnastics whole body movement with the goal of achieving consistent performance. Measurements are described using a movement cycle diagram to compare the differences between successful and unsuccessful executions. As another example, [17] monitors certain motor performance parameters of the rowing movement during a low intensity high volume training session to check if decline in the technique over this period.

In healthcare, for example, in [18], the authors investigate the gait pattern of patients suffering from Parkinson's disease and compare it to gait patterns of a healthy control group. Another study, [19], compares the gait pattern in Parkinson's disease patients on an off medication to establish the benefits of treatment.

The same type of analysis has gained attention in the last decades for the Sit-to-Stand movement. Early works on definitions and normative data presentation, such as [20, 21], provided the basis for studies on the deviations of this movement influenced by various conditions. For example, the work in [22] uses the Sit-toStand movement to investigate motor control and stability limitations on hemiplegic patients. Another study, [23], investigates the changes in strategies to execute the Sit-to-Stand due to obesity. Deviations of kinematics in frail elderly subjects when compared to healthy subjects make it possible to detect frailty and monitor the success of a rehabilitation program [24]. The success of a rehabilitation program for patients recovering from total knee arthroplasty can also be assessed using kinematic measurements during the Sit-toStand movement, such an example is presented in [25].

These are just a few examples from a vast literature on the recent developments using standardized and uniform descriptions for human movement measurements. Furthermore it indicates the relevance of studies in automatic human movement analysis and its potential applications.

2.2 HUMAN MOVEMENT MEASUREMENTS

Human movement measurement is a form of observation, through the use of devices, to describe phenomena in terms of variables to be analyzed. Data acquired from measurement systems may elucidate motor impairments after trauma or elucidate effects of controlled external intervention [26]. They are used to describe, characterize, measure the impact of external factors and analyze human movement. Kinematic and kinetic data may be combined and analyzed to explain movement features. Besides merely describing the movement, this process helps explain why a movement is executed in a particular way.

Along with the quality of the measurements, an important factor to consider in the choice of measurement devices for clinical application is the complexity in the measurement setup. Aspect such as: will the patient need to undress, are there markers to be placed, has the measurement device limited area coverage, among others need to be weighted when choosing a measuring device or setup[26].

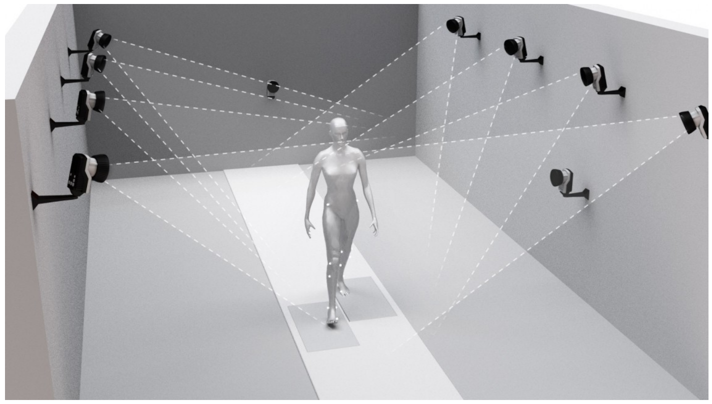
In human movement studies there are mainly three types of measurement variables: time, kinematic and kinetic. Time may be used alone to measure the duration of a certain movement, but it provides more information when associated with a kinematic or kinetic variable. Kinematic variables describe the movement of the body, they are either linear (displacement, velocity and acceleration) or angular (displacement, velocity and acceleration). Kinetic variables are either the force or force moment that generates the movement[26].

The devices considered gold standard for both linear and angular kinematic measurements are the infra-red marker-based multi-camera motion capture systems (MOCAP) from manufactures such as Vicon [1] or Qualisys[2]. Electronic goniometers, such as Biometrics[3], are also gold standard measurement devices for only angular kinematic variables.

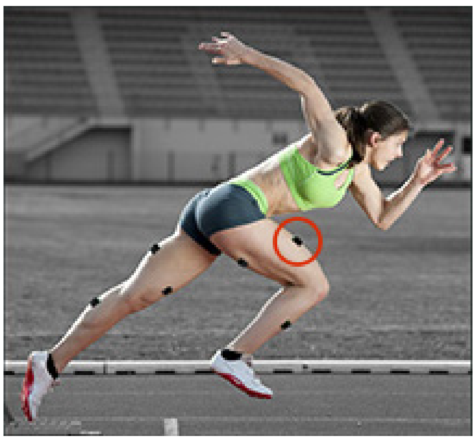
In recent years, there has been a constant development in low cost portable measurement devices for human movement. These devices are expected to make their way into clinics and homes to monitor movements from recovering patients during treatment or athletes in sport sessions [5] [27] [6][28].

Kinematic measures can be obtained with markerless optical-based MOCAP, such as the Microsoft Kinect [4] or Asus Xtion [5]. Coupled with dedicated software, they provide measurements in space representing the joints of a skeleton model for the human body. With these coordinates, it is possible to reconstruct the pose in terms of the linear and angular kinematic variables at each time frame. These vision-based devices have the advantage that no device needs to be attached to the user. But on the downside, they have a relative small coverage area, which limits the range of linear displacement. Also the software is made for

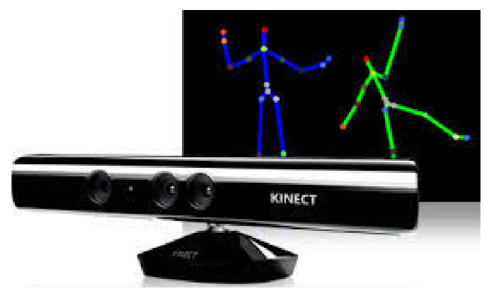
[1] http://www.vicon.com/System/Bonita
[2] http://www.qualisys.com
[3] http://www.biometricsltd.com/gonio.htm
[4] https://dev.windows.com/en-us/kinect
[5] https://www.asus.com/3D-Sensor/Xtion_PRO/



(a) Qualisys Marker-based Multi-camera MOCAP.



(b) Delsys Trigno IMU System.



(c) Microsoft Kinect Markerless Optical MOCAP.

Figure 2.2: Different MOCAP Devices.

stand up poses, movements with hip flexion are not well measured.

Another type of low cost MOCAP devices are the ones based on multiple inertial measurement units (IMU), such as Delsys [6], Yei[7] or XSens [8]. IMUs provide the angular orientation in reference to an absolute coordinate system. The reconstruction of angular kinematic data is done using a skeleton model of the human body. The advantage of IMU based measurement systems (compared to optical based) is the larger coverage area, which provides the user with more linear displacement. Although it is possible to estimate linear kinematic variables, the result is usually very inaccurate and degenerates with time. Therefore this type of MOCAP system is used to obtain only angular kinematic measurements. Another

[6]http://www.delsys.com/products/wireless-emg/

[7]https://www.yostlabs.com/yost-labs-3-space-sensors-low-latency-inertial-motion-capture-suits-and-sensors

[8]https://www.asus.com/3D-Sensor/Xtion_PRO/

disadvantage is the need to place multiple sensors in various body parts. Figure 2.2 shows examples of MOCAP devices.

As for kinetic variables, the most popular gold standard device is the force platform, such as Bertec[9]. Although stand alone force transducers also provide accurate and precise measurements, they require a dedicated physical structure to be mounted on, which limits their flexibility for different movement types.

A low cost option to obtain kinetic data is the Nintendo Wii Board [10]. This device uses sensors to estimate the resultant force applied in the board and its center of pressure, but not the orientation, as in the gold standard force platform.

Finally electromiography (EMG) signals are not kinematic or kinectic measurements, but they measure the muscle activity that causes human movement and are usually associated to kinematic or kinetic data in human movement analysis. Deslsys Trigno system is also able to provide EMG measurements, along with IMU data. Although not dealt with in this thesis, kinetic and EMG could be processed with the framework presented herein.

2.3 ASSESSMENT OF KINEMATIC AND KINETIC DATA

When kinematic or kinetic data is indexed with time, the result is a time-series of kinematic or kinetic measurements. The most common tool to analyze these time-series are the resulting graphs [1], because it is easier to visualize the movement pattern. The slope and curvature of the time-series graph indicate key features of a movement execution and provide a powerful tool for movement analysis. Figure 2.3 shows the angular displacement of the knee during one gait cycle on a treadmill. Analyzing the slopes and inflection points, it is possible to determine the beginning and end of each flexion or extension for this particular joint.

An extension of kinematic time-series graphs are the movement cycle diagrams [20]. Starting from the premiss that the same movement executed by different individuals will have a similar pattern and based on standardized and uniform definitions, time-series measurements of kinematic and kinetic data can be annotated for quantitative performance information extraction. Gait cycle diagrams are one of the most common example. Gait analysis is a well established field of study, mainly due to the use of the gait cycle diagram as a tool to describe, report and compare gait performance across different research findings (also due to the importance of gait movement). Because of the success of the gait cycle diagram, re-

[9]http://bertec.com/products/force-plates/
[10]http://wiifit.com

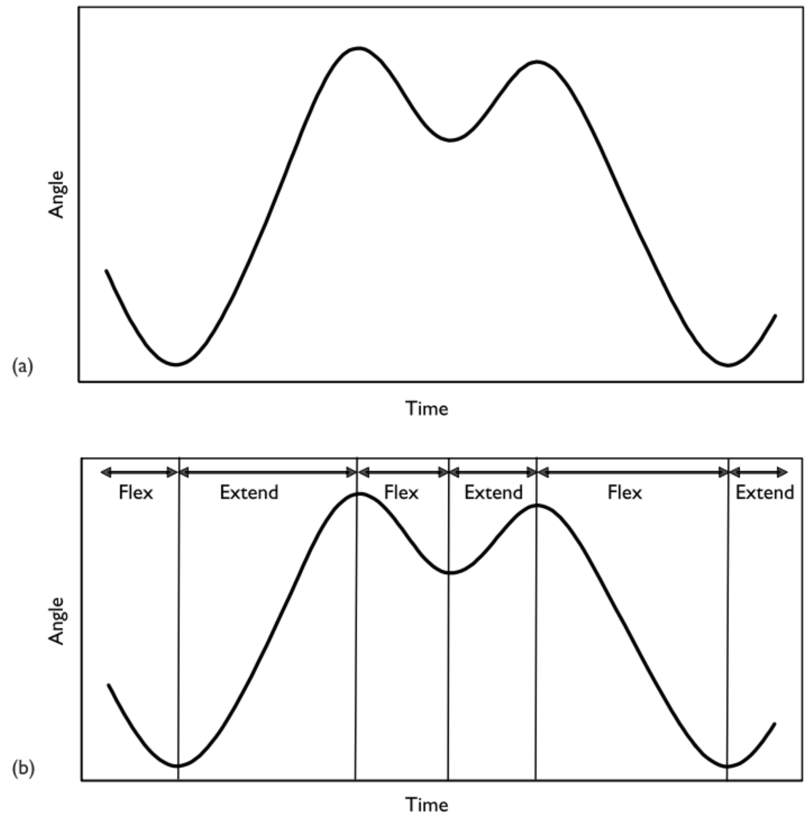
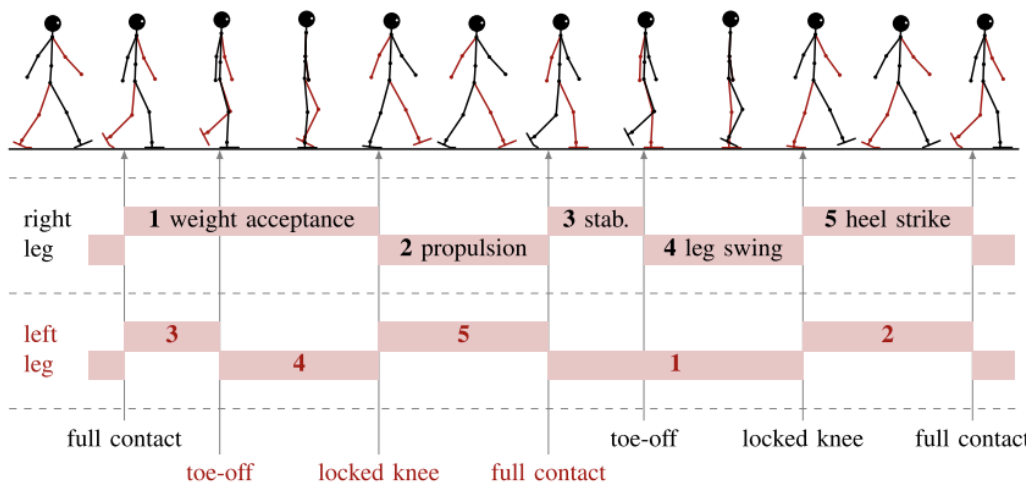


Figure 2.3: Time-series of knee angle measurements from a subject walking on a treadmill and the indication of changes in slope. Adapted from [1].

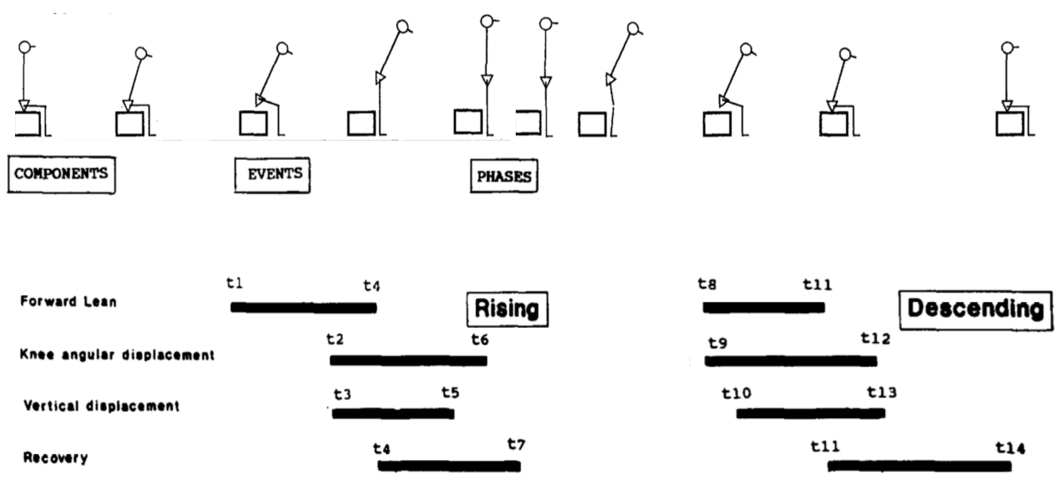
searchers have also proposed standardized descriptions for other movement types, such as the Sit-Stand-Sit movement [20] and also sport activities [1]. Figure 2.4 shows the movement cycle diagrams for gait and sit-to-stand-to-sit movements. Different kinetic and kinematic variables are used to determine the key moments used to describe each phase of the movement, so the generation of the movement cycle diagram usually requires multivariate measurement time-series.

In this section, we present the concepts and formal definitions from human movement analysis that are used to generate a movement cycle diagram and are the basis of our proposed method in Chapter 4. This includes definitions of what is considered a single movement entity and how we describe each movement in order to extract relevant spatiotemporal quantitative information in the scope of our study.

We delimit our study to a class of movements defined by [31, 32] as discrete movements. It is defined by [32] as: "a movement that has an unambiguously identifiable start and stop; discrete movements are bounded by distinct postures". An example of a discrete movement is standing from a chair: the start is marked by the siting posture and the stop is marked



(a) Gait movement cycle [29].



(b) Sit-Stand-Sit movement cycle (adapted from [20, 30]).

Figure 2.4: Examples of movement cycle diagrams.

by the standing posture. The movements used in the related works [33, 34] strictly fall in this class of movements. Throughout our work, the reference to one movement will refer to the motion executed between two postures. This distinction is made at this stage to restrict the scope of our work and avoid comparisons with methods that require a cyclic movement, such as the algorithms presented in the review [35]. But since our proposed method is inspired in the generation of the movement cycle diagrams, it can be used also to describe cyclic movements. However, we do not make any assumption about the cyclic nature of the movement.

One way to systematically describe one movement is to break it down into elements according to the change in the slope of kinematic and/or kinetic time-series, such as flexion and extension, of each body joint and its effects in posture changes.

We take the following definitions used by [20] to systematically describe discrete movements:

- *Events (e)* is a single identifiable occurrence of a change in the trend of the recorded movement pattern for each kinematic or kinetic variable.
- *Components (c)* are defined as those constituent parts of the movement, that are bounded by events within the same variable.
- *Phases (p)* are build from components and are also bounded by events, but the boundaries can be established using events from different variables.
- *Movement (m)* is a sequence of one occurrence of all phases between two distinct postures..

To clarify the meaning of these definitions, we take for example a sequence of two discrete movements: sit-to-stand and stand-to-sit shown in Figure 9.2. The kinematic measurements used to describe these movements are the knee angle and trunk tilt angle. The sit-to-stand movement is described in detail.

A movement cycle diagram displays the duration of each component of both the knee angle and the trunk tilt angle. The rising phase, as defined by [20], starts with the forward lean of the trunk and ends either with the full knee extension or full trunk extension, whichever occurs first. In our work the sit-to-stand movement is described with two phases: quiet siting and rising phase. The movement ends when the person reaches a full upright position. In a similar matter, the phases for the stand-to-sit movement are defined. The duration of each phase for both the sit-to-stand and the stand-to-sit movements are shown in a diagram in Figure 9.2, as well as the duration of each movement.

2.4 MATHEMATICAL BACKGROUND

This section provides the reader the basic concepts and a brief theoretical background on the mathematical representation and the estimation theory to be addressed in this thesis. We begin by recalling basic stochastic system concepts using state-space models and most common algorithms associated to filtering, smoothing and prediction. Particularly, we are interested in introducing the reader the concepts regarding switching linear dynamic systems.

For readers unfamiliar with stochastic systems or estimation theory, the general idea behind switching linear dynamics systems (SLDS) follows from combination of hidden Markov models with Kalman filtering for linear systems.

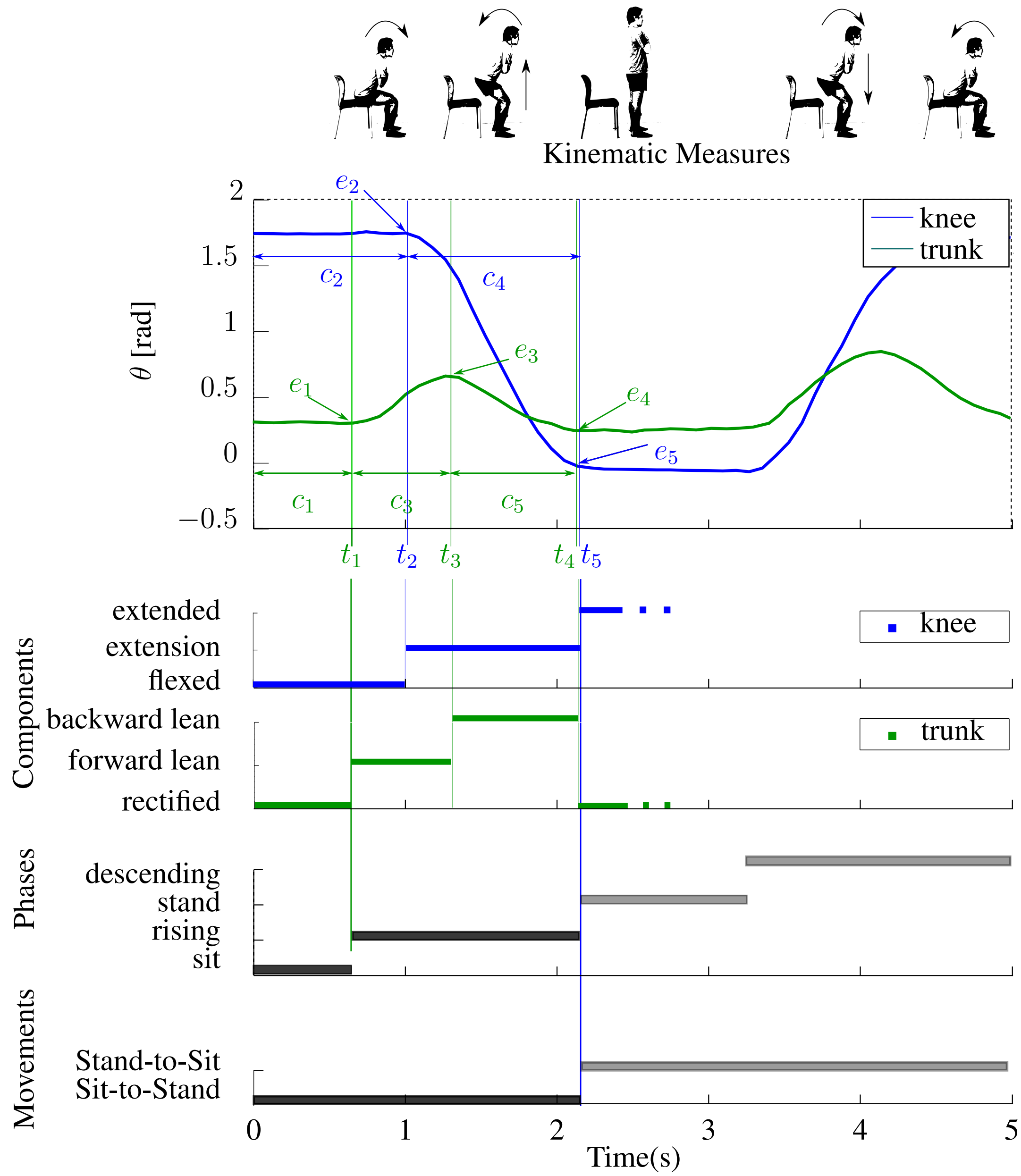


Figure 2.5: Movement description according to the definitions of events, components phases and movements. Each event (e) instant is marked with an arrow. For the knee angle there are two events (e_2, e_5): beginning and end of knee extension, which are also marked at t_2 and t_5. The interval between two events are the components (c) which are marked by double arrows. Events e_2 and e_5 form the component c_4. The events and components for the trunk tilt angle are defined analogously: there are three events e_1, e_3 and e_4 which are marked with arrows at t_1, t_3 and t_4, forming three components c_1, c_3 and c_5. Rising phase starts at with $e_1$and ends with e_5. Sit phase and rising phase makes the sit-to-stand movement.

Using hidden Markov models (HMMs), we are able to decode a sequence of discrete states—usually, discrete and finite—but we are unable to track the continuous values between the states. Think of it as a sequence of photographs, where we can estimate the sequence of poses that generated that sequence of photographs but we are unable to describe the movements between poses using a simple HMM. In contrast, the Kalman filter (KF) successfully tracks continuous linear movements over time—for instance, the KF can be used to track a particular body motion. We can think of an observer following the movement in a recorded film. However, only one model is used to represent the movement and this model is linear—consequently the Kalman filter can only track one simple and limited movement at a time. Moreover, since it is based on a single model, the technique is not suitable to segment a sequence of movements.

A switching linear dynamic system (SLDS), in essence, combines a hidden Markov model with Kalman filtering. So we can think of the basic elements of the SLDS as short movie of simple movements between two poses. By combining the sequence of these basic elements, we can represent a considerably more complex and complete movement. Since we know which set of basic elements are used to represent each movement, we can also use it to segment and recognize a sequence of movements in a given film and breakdown each movement to analyze critical poses or transitions.

In the light of this discussion—and, in contrast to the characteristic of existing movement analysis techniques—this thesis addresses and exploits the SLDS modeling in the development of the novel framework for movement analysis. In this sense, the mathematical developments presented in this section concerning SLDS provide the necessary background to fully understand the ideas and results that follows throughout the thesis and how the SLDS model fitting is employed in the context of movement analysis. Hence, readers are encouraged to read the whole section, even if they are already familiar to the notions and concepts presented herein.

2.4.1 State-Space Models

The state-space framework is a mathematical model used to represent a dynamic physical system based on a set of input, output and state variables related by first-order differential or difference equations. To abstract from the number of inputs, outputs and states, these variables are expressed as vectors which evolves over a time t based on a function $f(\cdot)$. The output of the system can be the state itself or a function of the state and input variables, that is,

$$\dot{x}(t) = f(t, x(t), u(t)),$$
$$y(t) = h(t, x(t), u(t)),$$

where x, y, and u denote the state, output and input vectors, and $x(0)$ defines the initial condition of the system. In the particular case where the dynamic system can be described by linear finite-dimensional invariant equations, the differential equation can be described in matrix form by

$$\dot{x}(t) = Ax(t) + Bu(t),$$
$$y(t) = Cx(t) + Du(t),$$

where the matrices A, B, C, D are known constant matrices that defines the dynamics of the system. In addition, throughout this manuscript, the dynamic system is assumed to be a sampled-based system where data is acquired at fixed intervals—sample time T. The evolution of a causal[11] linear state-space system can therefore be described by

$$x_{k+1} \triangleq x\left(T(k+1)\right) = Ax_k + Bu_k,$$
$$y_k = Cx_k + Du_k,$$

where x_k, y_k and u_k denote the state, output, and input vectors of the system at instant kT.

It is important to highlight that in more realistic scenarios, this model may not be perfectly accurate since the system dynamics is usually influenced by random noises and model uncertainties. Indeed, in practical applications, not only the dynamics of the system may be influenced by uncertainties and noises but the measurement process itself is liable to sensor errors and inaccuracies. To improve the estimation, tracking and control of the desired variables of interest, it is essential to address the disturbances as neglecting their influence would most likely lead to poor performance. In this case, the state and output variables x_k and y_k become random variables [36] and the system description becomes

$$x_{k+1} = Ax_k + Bu_k + r_k,$$
$$y_k = Cx_k + Du_k + w_k,$$

where r_k and w_k describe the system dynamics noise and the measurement noise. Throughout this thesis, we will assume that both noises are defined as Gaussian white noise, that is, they can be regarded as a sequence of uncorrelated Gaussian distributed random variables with zero mean and finite variance where the samples are independent with identical probability distribution (i.i.d.) [36].

[11] The system depends solely on the present and past states and inputs.

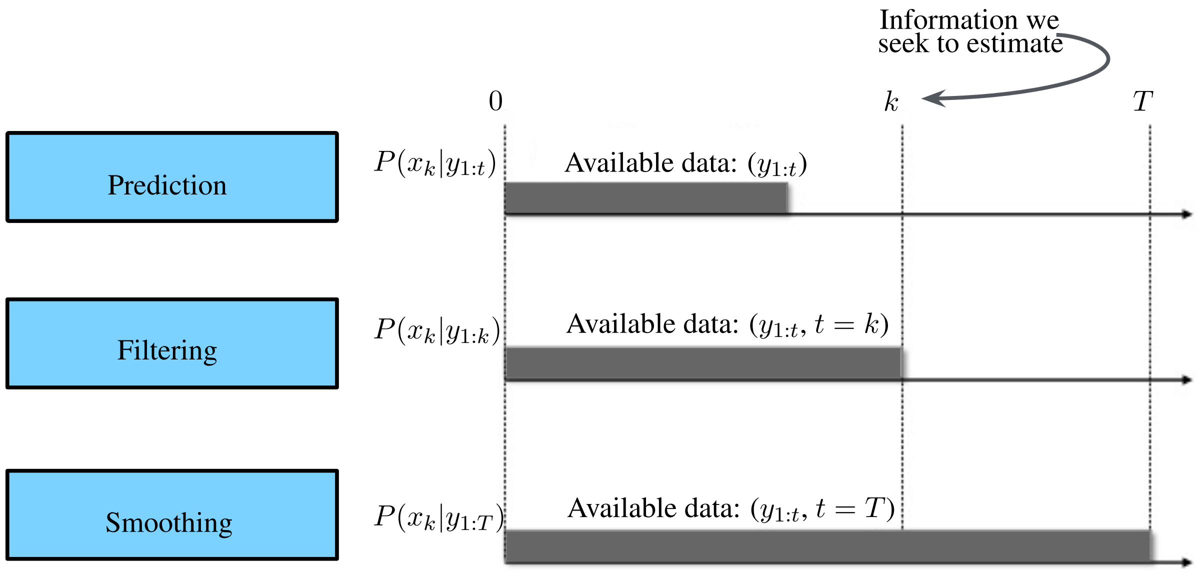


Figure 2.6: Estimation tasks.

In this thesis, we are particularly interested in analyzing a time-series of human movements measurements. This analysis can be done online where a new estimation is performed at each interaction—as soon as a new data is available—or offline where the analysis is performed only after the whole dataset is available.

The main advantages of the state space representation over related methods are: they can easily represent multivariate systems, they can easily incorporate prior knowledge and they do not suffer from finite window effect (frequency based models, such as the Fourier transform, are sensitive to sampling window during discretization) [37].

2.4.2 Estimation tasks in State-Space Models

To properly describe and estimate human movement, we are mainly interested in three estimation tasks based on a sequence of readings: prediction, filtering and smoothing, as illustrated in Figure 2.6. Additionally, in case that the state space is discrete—that is, considering only a discrete and usually finite set of data—there is also the task of estimating the most likely sequence of x that generated the observations y.

- **Prediction:** estimation of a future state, that is, to calculate the posterior probability distribution for a future state k, given all the observations up to the moment t: $p(x_k|y_{1:t})$, $0 < t < k$.[12]

[12] Throughout the manuscript the notation $y_{1:t}$ means that all values from y_1 up to y_t.

- **Filtering:** estimation of the current state, that is, to calculate the posterior probability distribution for the present state k, given all the observations up to the moment k: $p(x_k|y_{1:k})$.

- **Smoothing:** estimation of a past state, that is, to calculate the posterior probability distribution of an earlier state k, given all observations up to the moment T: $p(x_k|y_{1:T})$, $0 < k < T$.

- **Viterbi Decoding:** estimation of the most likely sequence of states that generated the sequence of observations: $argmax_{x_{1:k}} P(x_{1:k}|y_{1:k})$.

It is important to highlight that the above estimation tasks—as described—depend on whole available dataset. Hence, a large enough number of readings yields in soaring computational costs. Indeed, as $k \to \infty$, the estimation costs becomes unfeasible. To avoid soaring expenses, most estimation algorithms are based on stochastic process satisfying the Markov property. A stochastic process has the Markov property if the conditional probability distribution of future states of the process depends only upon the present state, not on the sequence of events that preceded it [38].

If the unknown—herein, we can also called hidden—state variable x is continuous—for instance, if $x \in \mathbb{R}$—we have a stochastic linear dynamic system (LDS). On the contrary, if x can assume solely a discrete set of values, we have a hidden Markov model (HMM) [39],[40],[41].

Filtering and Prediction The most common inference problem in online analysis is to recursively estimate the belief current state using Bayes' rule (see [42] for further information):

$$
\begin{aligned}
P(X_t|y_{1:t}) &\propto P(y_t|X_t, y_{1:t-1}) P(X_t|y_{1:t-1}) \\
&= P(y_t|X_t) \left[\sum_{x_{t-1}} P(X_t|x_{t-1}) P(x_{t-1}|y_{1:t-1}) \right]
\end{aligned}
$$

Using the Markov property, the problem can be considerably simplified by replacing $P(y_t|X_t, y_{1:t-1})$ with $P(y_t|X_t)$. Similarly, the one-step ahead prediction, $P(X_t|y_{1:t-1})$, can be computed from the prior belief state, $P(X_{t-1}|y_{1:t-1})$, because of the Markov assumption on X_t.

Therefore, based on the Markov assumption and its implications, recursive estimation consists of two main steps: predict and update. The predict step regards the estimation of

$P(X_t|y_{1:t-1})$, sometimes written as $\hat{X}_{t|t-1}$. Updating the expected mean value yields on computing $P(X_t|y_{1:t})$, sometimes written as $\hat{X}_{t|t}$. Once we have computed the prediction step, we can disregard the previous belief state: this operation is often called "rollup". Hence, the overall procedure takes constant space and time—which in turn implies time independence —per time step. This task is traditionally called "filtering", because we are filtering out the noise from the observations. However, in some cases the term tracking might also be employed when considering the dynamic filtering of a given variable.

Smoothing In opposite to the prediction and filtering, the smoothing task takes the whole dataset—that is all the information up to the current time T—to estimate a given state of the past, that is, compute $P(X_{t-l}|y_{1:T})$, where $l > 0$ is the lag variable that defines the size of the smoothing variable and $l < t < T$. This is traditionally called fixed-lag smoothing. Considering offline estimation, we can also consider all data up to the time t. This is called fixed-interval smoothing and corresponds to computing $P(X_t|y_{1:T})$ for all $1 \leq t \leq T$.

Viterbi Decoding Within Viterbi decoding (or computing the "most probable explanation"), the goal is to compute the most likely sequence of hidden states given the data, that is $x^*_{1:t} = argmax_{x_{1:t}} P(x_{1:t}|y_{1:t})$. Note that this is a different task than smoothing where only the most likely (marginal) state is estimated at each time t, as will be made clear in Section 2.4.3.3.

2.4.3 HMM

2.4.3.1 Model

A Hidden Markov Model (HMM) is a random variable automaton [41]. The discrete hidden state $x(t)$ (the random variable X_t) belongs to a discrete (usually finite) set $X_t \in \{1, \ldots, S\}$. The observation $y(t)$ (the random variable Y_t) may also belong to a discrete (usually finite) set $Y_t \in \{1, \ldots, L\}$, or it may be a continuous Gaussian distribution. The HMM model contains: a distribution for the initial state $\pi_{t=0}(s) = P(X_0 = s)$; a transition model Π, where Π is a stochastic matrix, which means that each element (i, j) represents the probability of transition from state i to state j at the instant t, i.e. $\Pi(i, j) = P(X_t = j|X_{t-1} = i)$; and an observation model, which can also be a stochastic matrix $B(y, i) = P(Y_t = y|X_t = i)$, in the case that Y_t is discrete. In the case that Y_t is continuous, the observation model will be a set of Gaussians $P(Y_t = y|X_t = i) = N(y; \mu_i, \Sigma_i)$, where μ_i represents the mean and Σ_i variance..

In an equivalent form, the HMM model can be written as

$$\begin{aligned} P(x_t|x_{t-1}) &= \boldsymbol{x}_t^T \Pi \boldsymbol{x}_{t-1}, \quad with \\ y_t &= B(y_t, x_t) \\ P(x_0) &= \pi_0 \end{aligned} \tag{2.1}$$

where $\boldsymbol{x}_t$ is a $1 \times S$ unit vector that indicates the index of the value x_t from the set $X_t \in \{1, \ldots, S\}$. Figure 2.7 is a graphical representation of the evolution of a HMM in (2.1).

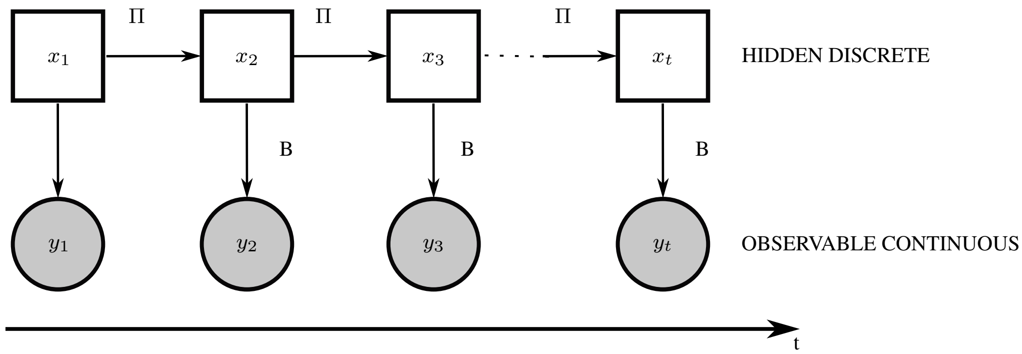


Figure 2.7: Graphical representation of a Hidden Markov Model.

The two most common tasks when using a HMMs are smoothing, which is usually done by the forward-backward algorithm, and estimation of the most likely sequence, which is done by the Viterbi algorithm [41].

HMMs are also widely used in many applications, such as speech recognition and sensor fault detection. In speech recognition Viterbi decoding is used to infer the sequence of letters of the spoken word from pre-processed audio measurements [43]. In fault sensor detection smoothing or filtering is used to check if the sensor readings are coherent with its expected behavior and operation limits [41].

2.4.3.2 Inference with Forwards-Backwards

Offline smoothing can be performed in an HMM using the well-known forwards-backwards algorithm (FB) [43]. In smoothing the whole observation dataset $y_t, t = 1 : T$ is available. Similar to filtering, the forwards-backwards algorithm uses prediction and update to estimate x_t based on y_t. However, it first predicts and updates x_t with the observations $y_t, t = 1 : T$ in the forwards pass. Next it refines the estimates of x_t going back in the observation dataset $y_t, t = T : 1$ in the backwards pass. Finally both the forward and backwards estimates are combined to get the estimates of each x_t based on the whole available observation dataset y_t...

The basic computation of the FB algorithm is to first recursively calculate, in the forwards pass from $t = 1 : T$, the forwards operator $\alpha_t(i)$ defined as:

$$\alpha_t(i) \triangleq P(X_t = i | y_{1:t})$$

Next, in the backwards pass from $t = T : 1$, the backwards operator $\beta_t(i)$, defined as:

$$\beta_t(i) \triangleq P(y_{t+1:T} | X_t = i)$$

is recursively calculated. Finally they are both combined to produce the combined operator γ_t, defined as:

$$\gamma_t(i) \triangleq P(X_t = i | y_{1:T})$$

to calculate the final estimate of each x_t.

The term $\gamma_t(i) \triangleq P(X_t = i | y_{1:T})$ can be expanded using Bayes rule, which results in:

$$P(X_t = i | y_{1:T}) \quad = \quad \frac{1}{P(y_{1:T})} P(y_{t+1:T} | X_t = i) P(X_t = i | y_{1:t})$$

but $\alpha_t(i) \triangleq P(X_t = i | y_{1:t})$ and $\beta_t(i) \triangleq P(y_{t+1:T} | X_t = i)$, therefore:

$$\gamma_t \propto \alpha_t . * \beta_t$$

where $.*$ denotes element wise product, i.e. $\gamma_t(i) \propto \alpha_t(i)\beta_t(i)$. In Sections 2.4.3.2 and 2.4.3.2 we will explain how to compute α_t and β_t.

The forward pass To compute α_t recursively in the forward pass, first we must elaborate the following equations: starting from the definition

$$\alpha_t(j) \triangleq P(X_t = j | y_{1:t}) = \frac{1}{c_t} P(X_t = j, y_t | y_{1:t-1})$$

where

$$P(X_t = j, y_t | y_{1:t-1}) = \left[\sum_i P(X_t = j | X_{t-1} = i) P(X_{t-1} = i | y_{1:t-1}) \right] P(y_t | X_t = j)$$

and

$$c_t = P(y_t | y_{1:t-1}) = \sum_j P(X_t = j, y_t | y_{1:t-1})$$

what c_t represents is the probability of the sequence of observations. In most cases it is just considered equal to one because the observations are taken as true.

Since the computation starts at $t = 1$, the equations are reduced to

$$\alpha_1(j) = P(X_1 = j | y_1) = \frac{1}{c_t} P(X_1 = j) P(Y_1 | X_1 = j)$$

or in the vector-matrix notation, this becomes

$$\alpha_1 \propto B\pi_0$$

where B comes from the HMM model, and π_0 is given. For each next time step, from $t = 2 : T$, α_t can be calculated as:

$$\alpha_t \propto B\Pi^T \alpha_{t-1}$$

where Π^T denotes the transpose of Π (from the HMM model).

The backwards pass To compute β_t in the backwards pass, we start at the end of the observation dataset, $t = T$. Since we have reached the end, $Pr(y_{T+1:T}|X_T = i) = Pr(\emptyset|X_T = i) = 1$ and therefore:

$$\beta_T(i) = 1$$

The recursive step is then:

$$\begin{aligned}
P(y_{t+1:T}|X_T = i) &= \sum_j P(y_{t+2:T}, X_{t+1} = j, y_{t+1}|X_t = i) \\
&= \sum_j P(y_{t+2:T}|X_{t+1} = j, y_{t+1}, X_t = i)P(X_{t+1} = j, y_{t+1}|X_t = i) \\
&= \sum_j P(y_{t+2:T}|X_{t+1} = j)P(y_{t+1}|X_{t+1} = j)P(X_{t+1} = j|X_t = i)
\end{aligned}$$

or using the vector-matrix notation:

$$\beta_t = \Pi B \beta_{t+1}$$

2.4.3.3 Inference with Viterbi

The target of Viterbi decoding (or computing the "most probable explanation"), is to find the most likely sequence of hidden states given the observation data:

$$x^*_{1:t} = argmax_{x_{1:t}} P(x_{1:t}|y_{1:t})$$

By the Bellman's principle of optimality, the most likely path to reach x_t consists of the most likely path to some state at $t-1$, followed by a transition to x_t. Hence we can compute the overall most likely path as follows. Similarly to the forwards-backwards algorithm, we introduce an operator, δ_t, for recursive computation:

$$\delta(j) \triangleq max_{x_{1:t-1}} P(X_{1:t} = x_{1:t-1}, X_t = j|y_{1:t}).$$

In the forward pass, starting from the first observation and moving towards $t = T$, we compute

$$\delta_t(j) = P(y_t|X_t = j) max_i P(X_t = j|X_{t-1} = 1)\delta_{t=1}(i).$$

This is analogous to the forwards pass of filtering, except we replace the sum with the corresponding maximum value. In addition we keep track of the identity of the most likely predecessor to each state:

$$\psi_t(j) = argmax_i P(X_t = j|X_{t-1} = i)\delta_{t-1}(i)$$

In the backwards pass, we can compute the identity of the most likely path recursively as follows:

$$x_t^* = \psi_{t+1}(x_{t+1}^*).$$

Viterbi decoding is different from forwards-backwards algorithm because it maximizes all the transitions $x_{t-1} \to x_t$ in the sequence resulting in the most likely path $x_{t=1:T}^*$, whereas forwards-backwards finds only the most likely (marginal) state x_t at each time t.

2.4.4 Linear Dynamic Systems

2.4.4.1 Model

In a Linear Dynamic System (without inputs) we assume that the random variables $X_t \in \mathbb{R}^{N_x}$, $Y_t \in \mathbb{R}^{N_y}$ and that the transition of the hidden state x_t and observation y_t at each time interval are linear Gaussian in the form:

$$\begin{aligned} P(X_t = x_t|X_{t-1} = x_{t-1}) &= N(x_t; Ax_{t-1} + \mu_X, Q) \\ P(Y_t = y_t|X_t = x_t) &= N(y_t; Cx_{t-1} + \mu_Y, R) \end{aligned} \tag{2.2}$$

Equations (2.2) can be written in the vector-matrix form, which is more recurrent in the literature:

$$\begin{aligned} \boldsymbol{x}_{t+1} &= A\boldsymbol{x}_t + \boldsymbol{r}_{t+1} \\ \boldsymbol{y}_t &= Cx_t + \boldsymbol{w}_t \end{aligned} \tag{2.3}$$

where $x_t \in \mathbb{R}^N$ is the hidden state of the state-space model, $r_t \quad (r \sim N(0, Q)$ is the state noise, $y_t \in \mathbb{R}^M$ is the observed measurement of the system, $w_t \quad (w \sim N(0, R)$ is the measurement noise. A is the state transition matrix and C is the observation matrix. The form in (2.3) is widely used in estimation and control theory.

In terms of LDS and regarding the three tasks (prediction, filtering and smoothing), the most famous and widely used algorithm with this model is the Kalman Filter, used for filtering in online applications such as navigation and sensor fusion. Prediction comes naturally using only the model for $x(t)$ in (2.3). Finally some algorithms are well stablished for smoothing, such as the Rauch-Tung-Striber smoother. Figure 2.8 is a graphical representation of the evolution of a LDS in (2.3).

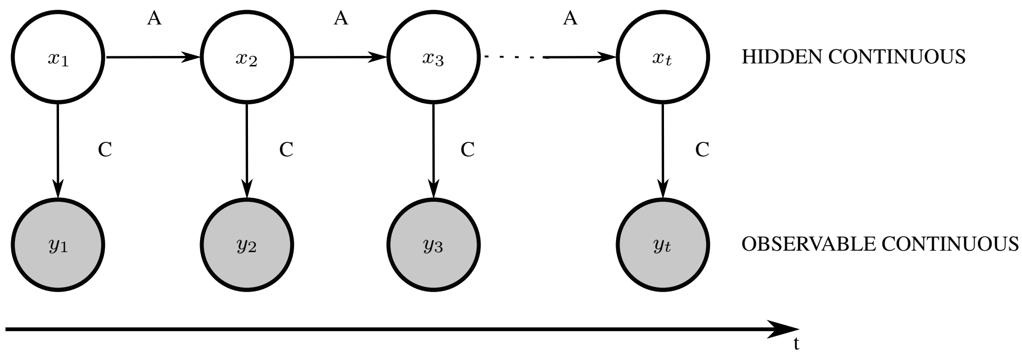


Figure 2.8: Graphical representation of a Linear Dynamic Systems.

2.4.4.2 Inference with Kalman Filter and RTS Smoothing

The equations for Kalman filtering / smoothing can be derived in an analogous manner to the equations for HMMs, except the algebra is somewhat heavier.

Forwards pass (Kalman Filter) Let us denote the mean and covariance of the belief state $P(X_t|y_{1:t})$ by $(x_{t|t}, \Sigma_{t|t})$. The forward operator,

$$(x_{t|t}, \Sigma_{t|t}, L_t) = Fwd(x_{t-1|t-1}, \Sigma_{t-1|t-1}, y_t; A_t, C_t, Q_t, R_t)$$

is defined as follows. First, we compute the predicted mean and variance

$$\begin{aligned} x_{t|t-1} &= Ax_{t-1|t-1} \\ \Sigma_{t|t-1} &= AV_{t-1|t-1}A' + Q \end{aligned}$$

Then we compute the error in our prediction (the innovation) e_t, the variance of the error S_t, the Kalman gain matrix K_t, and the conditional log-likelihood of this observation L_t:

$$\begin{aligned} e_t &= y_t - Cx_{t|t-1} \\ S_t &= C\Sigma_{t|t-1}C' + R \\ K_t &= V_{t|t-1}C'S_t^{-1} \\ L_t &= log\mathcal{N}(e_t; 0, S_t) \end{aligned}$$

Finally, we update our estimates of the mean $x_{t|t}$ and variance $\Sigma_{t|t}$:

$$\begin{aligned} x_{t|t} &= x_{t|t-1} + K_t e_t \\ \Sigma_{t|t} &= (I - K_t C)V_{t|t-1} = V_{t|t-1} - K_t S_t K_t' \end{aligned}$$

These equations are more intuitive than they may seem. For example, our expected belief about x_t is equal to our prediction, $x_{t|t-1}$, plus a weighted term, $K_t e_t$, where the weight $K_t = \Sigma_{t|t-1} C' S_t^{-1}$, depends on the ratio of our prior uncertainty, $\Sigma_{t|t-1}$, to the uncertainty in our error measurements S_t.

Backwards pass (RTS Smoothing) The backwards operator is defined as follows:

$$(x_{t|T}, \Sigma_{t|T}, \Sigma_{t-1,t|T}) = Back(x_{t+1|T}, \Sigma_{t+1|T}, x_{t|t}, \Sigma_{t|t}; A_{t+1}, Q_{t+1})$$

this is the analog of the γ recursion in Section 2.4.3.2. First we compute the following predicted quantities (or we could pass them in from the filtering stage):

$$\begin{aligned} x_{t+|t} &= A_{t+1} x_{t|t} \\ \Sigma_{t+1|t} &= A_{t+1} \Sigma_{t|t} A_{t+1}' + Q_{t+1} \end{aligned}$$

then we compute the smoother gain matrix

$$J_t = \Sigma_{t|t} A_{t+1}' \Sigma_{t+1|t}^{-1}$$

Finally, we can compute our estimates of the mean, variance, and cross variance $\Sigma_{t,t-1|T} = Cov[X_{t-1}, X_t | y_{1:T}]$

$$\begin{aligned} x_{t|T} &= x_{t|t} + J_t(x_{t+1|T} - x_{t+1|t}) \\ \Sigma_{t|T} &= \Sigma_{t|t} + J_t(\Sigma_{t+1|T} - \Sigma_{t+1|t}) J_t' \\ \Sigma_{t-1|T} &= J_{t-1} \Sigma_{t|T} \end{aligned}$$

these equations are known as the Rauch-Tung-Striebel (RTS) equations or RTS Smoother.

2.4.5 Switching Linear Dynamic Systems

A more recent development in State Space representation and estimation theory are the Dynamic Bayesian Networks (DBN) [37]. In this work we will focus on a specific type of DBN: the Switching Linear Dynamic System (SLDS). The main advantage of SLDS to our application is the fact that it combines both discrete and continuous hidden variables to model and extract information from a set of observations.

Switching Linear Dynamic System (SLDS) - also called in the literature Switching State-Space Models, Switching Kalman Filter Models or Jump-Markov Model - is a technique used to represent complex, non-linear systems through a combination of simpler linear state-space models [44], such as in (2.3). In this work we will give an overview of the main aspects of a SLDS, readers familiar with estimation theory who seek a better comprehension of SLDS should refer to [44, 37].

2.4.5.1 Model

A SLDS is composed of a set of linear state-space models, as presented in (2.3) in Section 2.4.4, associated to a switching variable $s_t \in \mathbb{S} := \{s_1, s_2, \ldots, s_S\}$($\mathbb{S}$ is finite and discrete). These linear state-space models can be written in the form:

$$\begin{aligned} \boldsymbol{x}_{t+1} &= A(s_{t+1})\boldsymbol{x}_t + \boldsymbol{r}_{t+1}(s_{t+1}) \\ \boldsymbol{y}_t &= C\boldsymbol{x}_t + \boldsymbol{w}_t, \quad with \\ \boldsymbol{x}_0 &= \boldsymbol{r}_0(s_0) \end{aligned} \tag{2.4}$$

where $x_t \in \mathbb{R}^N$ is the hidden state of the state-space model, r_t $(r(s_t) \sim N(0, Q(s_t))$ is the state noise, $y_t \in \mathbb{R}^M$ is the observed measurement of the system, w_t $(w(s_t) \sim N(0, R(s_t))$ is the measurement noise. $A(s_t)$ is the state transition matrix and C is the observation matrix, as in a conventional LDS.

The state transition matrix $A(s_t)$ and the measurement noise $r(s_t) \sim N(0, Q(s_t))$ in ((2.4)) are associated with a switching variable s_t, that indicates which model $(A(s_t), Q(s_t))$ is used at each time t.

Additionally, the switching variable, s_t, evolves in time according to the model:

$$\begin{aligned} P(s_{t+1}|s_t) &= \boldsymbol{s}_{t+1}^T \Pi \boldsymbol{s}_t, \quad with \\ P(s_0) &= \pi_0 \end{aligned} \tag{2.5}$$

where $\boldsymbol{s}_t$ is a $1 \times S$ unit vector that indicates the index of s_t in the set $\mathbb{S}$. The state transition matrix Π, whose elements are $\Pi(a, b) = P(s_{t+1} = s_a|s_t = s_b)$, represents the probability of $s_{t+1} = s_a$, given that $s_t = s_b$. Figure 2.9 is a graphical representation of the evolution of a SLDS in (2.4) and (2.5).

The SLDS approach develops the stochastic algorithms for learning the parameters of the models (2.4) and (2.5) (specially $A(s_a), Q(s_a), \Pi$) and estimating s_t, x_t from the observed measurements in a time-series, combining two well known probabilistic approaches: LDS (Kalman Filter) and HMM (forward-backward and Viterbi algorithms). The complexity of

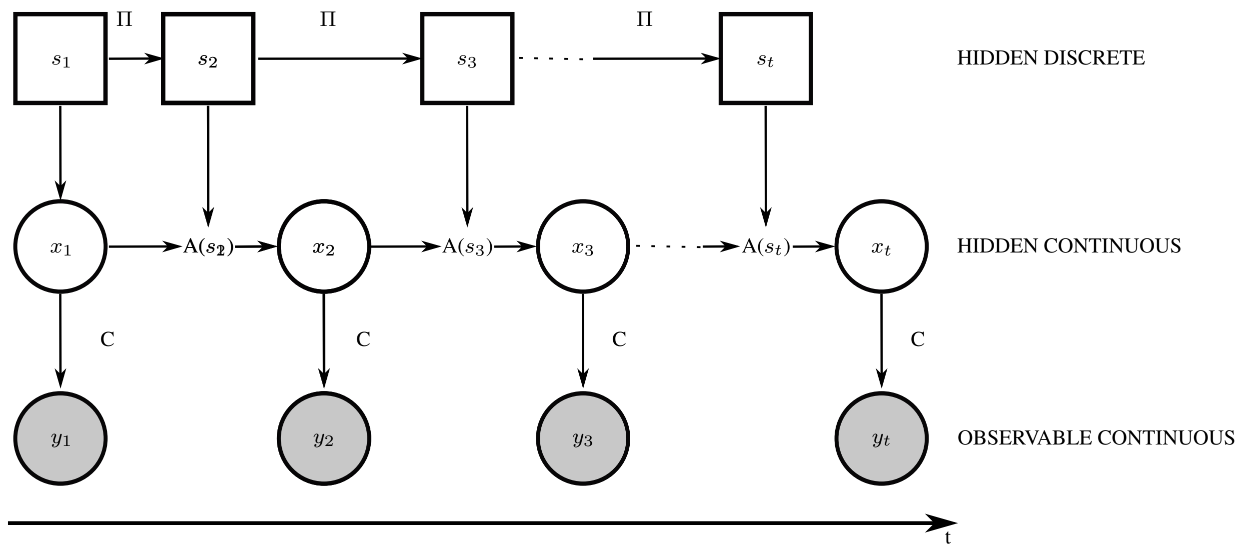


Figure 2.9: Graphical representation of a Switching Linear Dynamic System.

the estimation tasks (filtering, smoothing or finding the most likely sequence) in SLDS compared to either LDS or HMM lies on the need to estimate two hidden variables, i.e. s_t, x_t, simultaneously.

The evolution of the time-series in each interval $[t, t+1]$ is tracked with a linear state-space model as in Equation (2.4); i.e the values of $A(s_{t+1})$ and $r_{t+1}(s_{t+1})$ are associated with the value of $s \in \mathbb{S}$. Tracking a given time-series with SLDS will yield a sequence of symbols s_t that best represent the time-series trends.

Working with SLDS models, it is possible to execute the usual tasks involved in state space representations: prediction, filtering, smoothing and finding the most likely sequence of discrete events.

In order to estimate the most likely sequence based on observed time-series, [44] proposes an adaptation of the Viterbi algorithm, commonly used in HMM, for the SLDS case. This algorithm relies on a cost function ($\mathcal{C}$) that considers both the tracking error of the linear state-space variable x_t in ((2.4)) and the cost of the transitions for the discrete switching variable s_t in (2.5).

The method that will be presented in Chapter 4 relies mainly in the algorithm proposed by [44] and henceforth, we will refer to this algorithm as SLDS-Viterbi.

2.4.5.2 Inference with Approximate Viterbi

The goal of inference is to estimate the posterior of the hidden states of the system (s_t and x_t) given some known sequence of observations $y_{1:T}$ and the known model parameters.

If there were no switching dynamics, the inference would be straight forward - we could infer $x_{1:T}$ from $y_{1:T}$ using LDS inference (Kalman Filter or RTS Smoothing). However the presence of switching dynamics embedded in matrix Π makes exact inference impractical.

To see that, assume that the initial distribution of x_0 at $t = 0$ is Gaussian, at $t = 1$ the pdf of the physical system state x_t becomes a mixture of S Gaussians pdfs since we need to estimate over S possible but unknown plant models at time t. It is clearly an intractable problem even for moderate sequence lengths. So, it is more plausible to look for an approximate, yet tractable, solution to the inference problem.

The task of Viterbi approximation approach is to find the best sequence of switching states s_t and LDS states x_t that minimizes the cost for $x_{1:T}, s_{1:T}, y_{1:T}$ ([44] uses a Hamiltonian cost function). It is well known how to apply Viterbi inference to discrete state HMMs and for continuous state Gauss-Markov Models (LDS). An algorithm for Viterbi inference in SLDSs is proposed by [44] and described next.

Define first the "best" partial cost up to time t of the measurements sequence $y_{1:T}$ when the switch is in state i at time t:

$$\mathcal{C}_{t,i} = min_{S_{t-1},\mathcal{X}_t} H(\{S_{t-1,}, s_t = e_i\}, x_t, y_t)$$

Namely, this cost is the least cost over all possible sequences of switching states S_{t-1} and corresponding LDS states $\mathcal{X}_T$. This partial cost is essential in Viterbi-like total cost minimization.

For a given switch state transition $j \rightarrow i$ it is possible to establish the relationship between the predicted and filtered estimates. From Kalman estimation we can use the equations to predict and update each transition $j \rightarrow i$.

Each of these transitions $j \rightarrow i$ has a certain innovation cost $\mathcal{C}_{t,t-1,i,j}$ associated with it, as defined in

$$\mathcal{C}_{t,t-1,i,,i} = \frac{1}{2}(y_t - C\hat{x}_{t,t-1,i,j})'(C\Sigma_{t,t-1,i,j}C' + R)^{-1}(y_t - C\hat{x}_{t,t-1,i,j}) + \frac{1}{2}log|C\Sigma_{t,t-1,i,j}C' + R| - log\Pi(i,j) \tag{2.6}$$

One portion of the innovation cost reflects the LDS state transition (similar to the Kalman Filter). The ramaining portion is due to switching from state j to state i, $log\Pi(i, j)$ from the Forwards-Backwards HMM algorithm.

Obviously, for every current switching state i there are S possible previous switching states where the system could have originated from. To minimize the overall cost at each time step t and for every switching state i one "best" previous state j is selected:

$$\begin{aligned} \mathcal{C}_{t,i} J_{t,i} &= min_j \{\mathcal{C}_{t,t-1,i,j} + \mathcal{C}_{t-1,j}\} && (2.7) \\ \psi_{t-1,i} &= argmin_j \{\mathcal{C}_{t,t-1,i,j} + \mathcal{C}_{t-1,j}\} && (2.8) \end{aligned}$$

The index of this state is kept in the state transition record $\psi_{t-1,i}$. Consequently, we now obtain a set of S best filtered LDS states and variances at time t:

$$\begin{aligned} x_{t|t,i} &= \hat{x}_{t|t,i,j,\psi_{t-1,i}} \\ \Sigma_{t|t,i} &= \Sigma_{t|t,i,\psi_{t-1,i}} \end{aligned} \tag{2.9}$$

Once all T observations $y_{1:T-1}$ have been fused the best overall cost is obtained as

$$\mathcal{C}^*_{T-1} = min_i \mathcal{C}_{T-1,i}$$

To decode the "best" switching state sequence one uses the index of the best final state

$$i^*_{T-1} = argmin_i \mathcal{C}_{T-1,i} \tag{2.10}$$

and then traces back through the state transition record $\psi_{t-1,i}$, as:

$$i^*_t = \psi_{t,i^*_{t+1}} \tag{2.11}$$

The switching model is decoded. Given the "best" switching state sequence the sufficient LDS statistics can be easily obtained using the RTS smoothing, for example:

$$\langle x_t, s_t \rangle = \begin{cases} \hat{x}_{t,T-1,i^*_t} & i = i^*_t \\ 0 & otherwhise \end{cases}$$

for $i = 0, \ldots, S-1$.

The algorithm for the Viterbi inference for SLDS can now be summarized in Algorithm 2.1.

2.4.5.3 Inference Online Forwards-Backwards

The Viterbi inference requires the whole sequence $y_{1:T}$ and therefore is suited for offline processing. For online processing, the concepts from the Kalman Filter and Forwards-Backwards algorithms may be applied to the Algorithm 2.1. In [37], a few insights are given for this adaptation, although the online inference algorithm is not clearly stated.

Algorithm 2.1 SLDS Viterbi inference algorithm

Initialize the state estimates $\hat{x}_{0|-1,i}$, and covariation matrix $\Sigma_{0|-1,i}$ for all S models;
Initialize the transition cost $\mathcal{C}_{0,i}$;
for $t = 1 : T - 1$
    for $i = 1 : S$
        for $j = 1 : S$
            Predict and update (Kalman Filter) $\hat{x}_{t|t,i,j}$ and $\Sigma_{t|t,i,j}$ for the state-space model i
            Calculate the innovation cost $\mathcal{C}_{t|t-1,i,j}$ using (2.6)
        end
        Get the minimum partial cost $\mathcal{C}_{t,i}$, as in (2.7)
        Get the minimum argument for $\psi_{t-1,i}$ as in (2.8)
        Get the state-space model estimates $\hat{x}_{t|t,i}$ and $\Sigma_{t|t,i}$ using (2.9)
    end
Get the switching state i^*_{T-1} with the least cost, as in (2.10);
Backtrack to maximize the switching state sequence i^*_t, using (2.11)

The basic idea is to execute a fixed lag smoothing in interval $t : t + L, \quad L > 0$, using prediction from KF and the forwards backwards operands from FB. Instead of performing the forward pass to the whole sequence, it is only applied from time t up to t+L. Then from time $t + L$ the backward pass is executed back to time t. Finally the "best" switching state sequence is backtracked in the interval $t : t + L$, that is: $i*_{t:t+L}$. Clearly, if $L = 1$, the algorithm is reduced to a filtering algorithm and is suitable for inline inference. The fixed lag smoothing algorithm for SLDS is presented in Algorithm 2.2.

Algorithm 2.2 SLDS Smoothing/Filtering inference algorithm

Initialize the state estimates $\hat{x}_{0|-1,i}$, and covariation matrix $\Sigma_{0|-1,i}$ for all S models;
Initialize the transition cost $\mathcal{C}_{0,i}$;
for $t = 1 : T$
  for $t = t : t + L$
    for $i = 1 : S$
      for $j = 1 : S$
        Predict and update (Kalman Filter) $\hat{x}_{t|t,i,j}$ and $\Sigma_{t|t,i,j}$ for the state-space model i
        Calculate the innovation cost $\mathcal{C}_{t|t-1,i,j}$ using (2.6)
      end
      Get the minimum partial cost $\mathcal{C}_{t,i}$, as in (2.7)
      Get the minimum argument for $\psi_{t-1,i}$ as in (2.8)
      Get the state-space model estimates $\hat{x}_{t|t,i}$ and $\Sigma_{t|t,i}$ using (2.9)
    end
  end
  Get the switching state i^*_{t+L} with the least cost, as in (2.10);
  Backtrack to maximize the switching state sequence $i^*_{t:t+L}$, using (2.11)
end

Human motion measurement systems proliferated in the last decades. From the gold standard multi-infrared-camera systems to the low cost portable systems, such as the Microsoft Kinect or inertial sensors, obtaining precise kinematic human data today is affordable and widespread [8, 5]. However, the post-processing techniques for automatic spatiotemporal feature extraction from kinematic data are still emerging. Figure 3.1 represent this workflow.

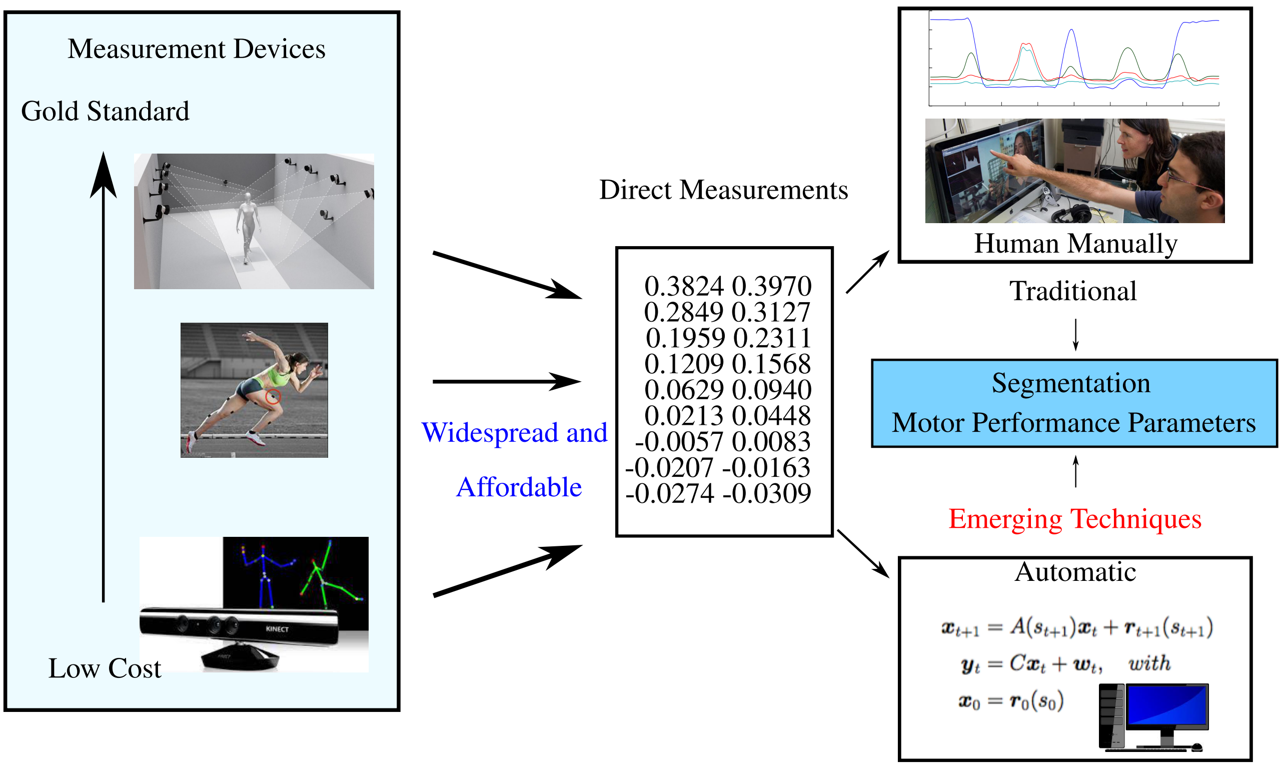


Figure 3.1: Workflow of measurement systems and feature extraction.

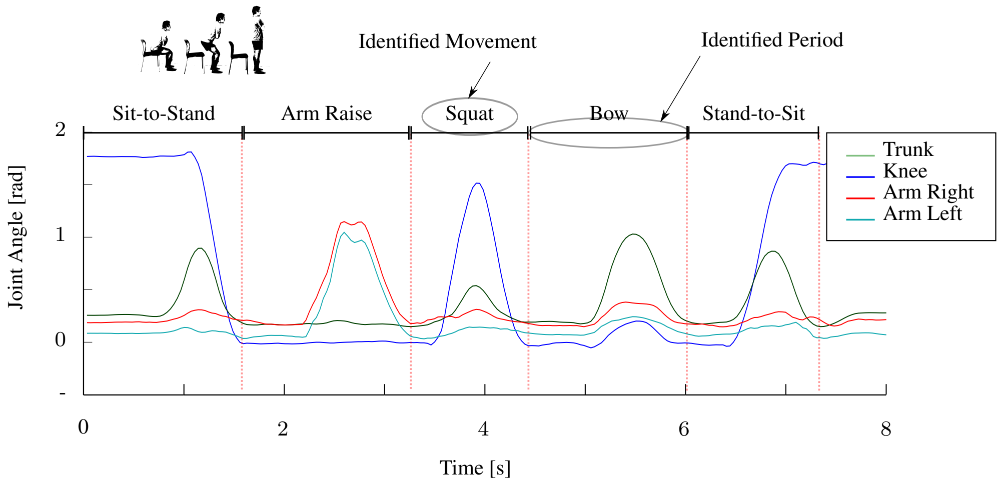
In the context of human motion segmentation and classification , an important distinction must be made about the meaning of the task of segmentation and classification. One problem is to segment a sequence of unknown movements into single executions followed by the classification of movement type (labeling each single execution according to a set of possible candidates), as illustrated in Figure 3.2a. This problem has been recently investigated with important results such as done by [33] and [34]. Another problem is: given a single execution (or a repetitive sequence) of a known movement type (a sequence of steps, or a sequence of sit-stand-sit), pinpoint the key events in order to extract useful information, i.e. spatiotemporal features, as illustrated in Figure 3.2b. The framework proposed in this thesis and presented in Chapter 4 deals with both problems.

Recent works in the scope of this work can be separated in two groups based on the task addressed: movement segmentation (including or not movement type recognition)[45, 46, 33, 34] or motor performance parameters extraction [45]. A variety of sensors, variables and techniques have been proposed to solve these tasks. Table 3.1 gives an overview of recent works according to signal processing techniques and task addressed.

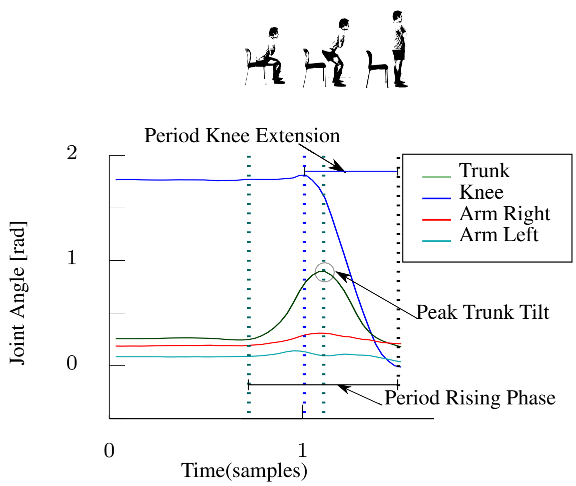
3.1 AUTOMATIC SEGMENTATION OF HUMAN MOVEMENT

For the segmentation task, the method proposed in [46] uses Dynamic Time Warping (DTW) and data from a single inertial sensor mounted on the back of a person to automatize the segmentation of the commonly used Timed Up and Go (TUG) test [47]. DTW is a technique to find optimal alignment between two time series. DTW is used to align the measured movement sequence to the template model in order to determine the moment of transition between each movement type that compose the TUG test: sit-to-stand, gait, 180^o turn and stand-to-sit. This approach has the advantages that DTW requires less tuning and smaller training data set (compared to other modeling techniques, such as Hidden Markov Models, HMM). However, this DTW model is very specific: one template models the whole sequence of movements. Moreover, the description of each movement is ad hoc: peaks in the yaw axis indicate the 180^oturns; and peaks in the pitch axis indicate the sit-to-stand and stand-to-sit movements. This technique was validated on ten healthy subjects and twenty Parkinson's disease patients.

Another work, presented in [34], proposes a key pose identification algorithm that combines a series of statistical classifiers (such as Support Vector Machines and Naive Bayes) and specifically designed functions. This algorithm detects desired static poses in a data set and uses it to align the time-series to a previously trained template. Movement sequences are captured from a Microsoft Kinect device to represent body motions as multiple joints angles. The templates for the desired static poses are modeled from a manually annotated data set which are encoded with a specific developed function to so called motion signatures. Frame-wise features from the motion signatures are extracted and learned by statistical classifiers. Using the trained templates and the same statistical classifiers, the desired static poses are detected in new time-series. The advantage of this method is that the models can be refined with a new data set and improves the performance of the algorithm. On the downside, this technique models only one movement type at a time and is suitable to segment only a repetitive sequence of the same movement. This technique was validated on seven healthy adult subjects.



(a) Segmentation.



(b) Spatiotemporal features.

Figure 3.2: Example of the segmentation and the motor performance parameters extraction tasks. (a) Segmentation task: to determine the beginning and end of each movement (movement period) of a Sequence of Mixed Movements: Sit-to-Stand, Arm Raise, Squat, Bow and Stand-to-Sit. If the sequence is not predefined, there is the additional sub-task of determining each movement type. This segmentation result was obtained with the proposed method. (b) Motor performance parameters extraction (peak trunk tilt, knee extension period and rising phase period) for the Sit-to-Stand movement.

Table 3.1: Comparison Between Previous Works and Proposed approach

Reference	Sensor	Dimension	Variable(s)	Movements	Segmentation	Recognition	Parameter extraction	Online / Offline
Salarian2010[45]	IMU(accel+gyro)	Univariate	Trunk, shank, thigh (one for each movement)	TUG	Specific designed math function	-	Specific procedure for each motion type	Offline
Adame2012[46]	IMU(Gyro)	Univariate	Pitch(sit-stand),yaw(turn)	TUG	DTW	-	-	Offline
Dios2014[34]	Kinect	Multivariate	Multiple joint angles	Various Discrete Movements	Key pose ID algorithm (Statistical classifiers+motion signature)	-	-	Online
Lin2014[33]	IMU, Optical Motion Capure	Multivariate	Multiple joint angles, accelerometer	Various Discrete Movements	ZVC	HMM, DTW	-	Online
Proposed Approach 2016	IMU(accel)	Multivariate	Multiple joint angles	Various Discrete Movements	SLDS	SLDS	SLDS	Online

Movement type recognition along with segmentation is handled in the approach presented in [33]. A combination of Zero Velocity Crossing (ZVC) and HMM is proposed for online segmentation and movement type recognition, respectively, based on kinematic measures from multiple joint angles. Different experiments with varied sensors (optical MOCAP and portable IMUs) were used to obtain the data set. An automatic procedure for template training based on traditional ZVC and HMM methods is presented. The templates are then used for online segmentation and movement type recognition. This approach has the advantage of modeling different movement types that can be executed in any random sequence. However, the model training procedure involves manually setting a few thresholds to avoid over-segmentation. The validation was carried out in three different scenarios, two with healthy subjects only (twenty one total) and one with four patients undergoing rehabilitation after total knee joint replacement. The healthy subjects executed different sequences of whole body movements. On another scenario, the patients executed a knee extension while seated, which is a simple, one degree of freedom movement.

Furthermore, no motor performance parameters were extracted within each movement execution in [46, 34, 33], only the total movement duration, which comes directly from segmentation.

3.2 AUTOMATIC MOTOR PERFORMANCE PARAMETER EXTRACTION FROM HUMAN MOVEMENT

Regarding problem of pinpointing events in a known movement type the few current solutions are specifically designed for each application: i.e. they depend on the type of sensor, on the motion executed, and/or ignore standard biomechanics descriptions [5]. These approaches limit the use of baseline data and results from previous studies to assess the quality of the motion. Besides, performance comparison among techniques is impossible because of their specificity.

Motor performance parameter extraction is achieved in [45] for the TUG test with measurements from inertial sensors placed in the forearms, shanks, thighs and sternum. The TUG sequence is segmented using specific functions and subsets of sensors to detect each movement type (sit-to-stand, gait, 180^o turn and stand-to-sit). Next, motor performance parameters (such as trunk range of motion and peak velocity during sit-to-stand) are extracted analyzing each movement type separately. Likewise, a combination of another set of specific functions and subset of sensors calculates the relevant parameters for each movement type. data set from twelve subjects in early stage of Parkinson's disease and twelve healthy control subjects were used for validation. The highlight of this work is that it was already proved to work on healthy and impaired subjects. The drawback is that it involves specific and ad hoc solutions for each movement type, considerably reducing ease-of-use by the non-expert user.

To the best of our knowledge, an integrated solution for both segmentation and motor performance parameters extraction using the same technique has not yet been proposed.

4 SLDS FOR AUTOMATIC HUMAN MOVEMENT ANALYSIS

4.1 TRANSLATING STANDARD DEFINITIONS TO SLDS ELEMENTS

Within the current state of the art there is a lack of methods that successfully represent human movement measured by arbitrary sensors and simultaneously enables segmentation and motor parameter extraction. The first contribution of this thesis involves the integration of tools described in Chapter 1 and their combined use for such tasks.

In this section, we show that SLDS (Section 2.4.5) directly fits the definitions of human movement analysis given in Section 2.3 and solves the two tasks (segmentation and motor parameter extraction) in a systematic unified way. Recall from Chapter 3, that a solution for the problem of using a single signal processing technique for both tasks has not been yet proposed.

To achieve this goal, it is necessary not only to analyze the behavior of all kinematic variables simultaneously, but also look at each variable separately. Analyzing all kinematic variables at the same time is useful to represent the overall movement pattern which is necessary to achieve the segmentation task. This represents the coordinated actions of different body parts that results in what we call one movement type. One example is the pattern of trunk and legs flexion and extension necessary to execute the sit-to-stand movement. However, extracting motor performance parameters requires a specific analysis of each kinematic variable. For example, to extract the peak trunk inclination during the sit-to-stand movement, we must analyze only the kinematic variable trunk angle. An overview is given in Figure 4.1.

We present our method by first describing in Section 4.1.1 a scalar SLDS model -which means that x_t and y_t in the SLDS model (2.4) are scalars - that will be used to detect changes in trend to pinpoint events and determine the components for each kinematic variable as shown in Section 2.3. Next, we describe a multidimensional SLDS - formed with the combination of the scalar SLDS models - to track all variables simultaneously that will be used to determine the start and end of each movement and also recognize which movement is executed.

4.1.1 Scalar SLDS Model for Motor Performance Parameters Extraction

Spatiotemporal features of a single kinematic variable, as illustrated in Figure 4.1, may be computed using an scalar (or univariate) SLDS model.

In the proposed SLDS representation, an event (e) is a change in the symbol (s_t) in the switching variable sequence. A component (c) is a sequence of repetitive symbols $(1, 1, ..., 1)$. For example, the sequence $(1, 1, 1, 2, 2, 2)$ has one event and two components. A phase (p) is delimited by two events possibly in two different variables. In the sit-to-stand example, shown in Figure 4.1, the rising phase starts with the beginning of the trunk forward lean (an event in the kinematic variable trunk tilt) and ends with the full knee extension (an event in the kinematic variable knee angle).

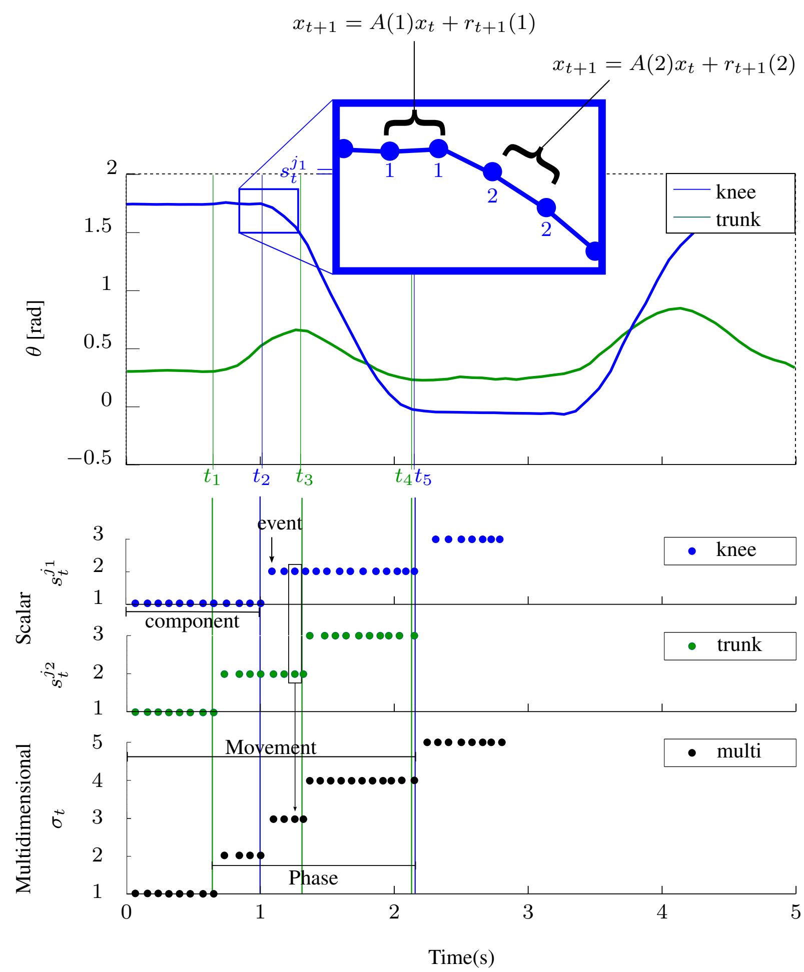


Figure 4.1: SLDS model. One event and component are marked in the scalar model ($s_t^{j_1}$). One movement, and one multidimensional symbol (σ_t) and its corresponding scalar symbols are also indicated. The result in this figure was obtained with the proposed method.

Given a sequence of measurements from one kinematic variable y_t (angle joints, in our case) in time , the problem becomes estimating the most likely sequence for the switching variable s_t associated with this time series as well as the most likely corresponding switching state x_t. In other words: we have physical measures of a motion for a given body part (knee angle, for example) and we wish to infer which sequence of actions (knee flexion/ extension, for example) generated those physical measures.

The estimation of the sequence of symbols $s_t, 1 < t < T$ (T is the length of the time-series), from a scalar time-series with a SLDS requires a set of linear state-space models $A(s_t), Q(s_t)$ as in (2.4). In this work, a constant-velocity model has been selected as an initial candidate for representing different motion dynamics. A constant velocity ($v(s_t)$) affine state-space form represents each state-space model and (2.4) is explicitly written as:

$$\begin{aligned} x_{t+1} &= \begin{bmatrix} 1 & v(s_{t+1}) \end{bmatrix} \begin{bmatrix} x_t \\ 1 \end{bmatrix} + r_{t+1}(s_{t+1}) \\ y_t &= \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_t \\ 1 \end{bmatrix} + w_t. \end{aligned} \tag{4.1}$$

The hidden state x_t and the observed measurement y_t may represent joint angle measurements, contact force readings, or any other variable related to human motion. The constant velocity term ($v(s_t)$) is the factor that indicates the trend in the time-series within the interval $[t, t+1]$, i.e. in each time step. For instance, in terms of joint angles ($v(s_t)$) is the term in $A(s_t)$ that represents either angular motion (such as flexion or extension) or hold of a static position (no angular motion), as well as its intensity.

Another key element in a SLDS is the transition matrix Π in (2.5). Both the constant velocity factor ($v(s_t)$) in (4.1) and the transition matrix Π in (2.5) enable the representation of the typical succession of flexion, extension or static pose in each joint ($j_i \in \mathcal{J} := \{j_1, ..., j_J\}$) for each movement type ($\tau_n \in \mathcal{T} := \{\tau_1, ..., \tau_N\}$). Explanations on how to estimate terms ($v(s_t^{j_i})$) and Π using labeled training dataset are provided in Section 4.2.

The example in Figure 4.1 elucidates the relationship between SLDS and the definitions of events (e), components (c) and phases (p). A snippet zoom of the knee angle curve demonstrate the representation of this time-series in terms of an scalar SLDS. The first two samples in the zoomed area represents $s_t^{j1} = 1$, which corresponds to the linear state space model $A^{j_1}(1)$, and the following two terms are represented by $s_t^{j_1} = 2$, $A^{j_1}(2)$. Physically, this zoomed area represents the event "beginning of knee extension", which delimits the components "knee flexed" and "knee extension". Figure 4.1 also presents the estimated sequence for the whole Sit-to-Stand movement.

Specifically for the knee (j_1) angle switching variable ($s_t^{j_1}$), we have the following representation: knee statically flexed ($s_t^{j_1} = 1$), knee extension ($s_t^{j_1} = 2$) and knee statically extended ($s_t^{j_1} = 3$). The first event and component for the knee angle are annotated. In addition, the estimated sequence for the trunk angle (j_2) switching variable ($s_t^{j_2}$) is presented. Using the scalar SLDS representation for each kinematic variable ($y_t^{j_i}$) it is now possible to automatically describe one movement in terms of events (e), components (c) and phases (p).

4.1.2 Multidimensional SLDS Model for Segmentation

Next, we consider a multidimensional SLDS model that tracks all the kinematic variables simultaneously. This multidimensional SLDS model is a combination of all scalar SLDS models (A^{j_i}) described in Section 4.1.1 that represent, for instance, each joint angle (j_i).

The multidimensional observed measurements ($\boldsymbol{y}_t$) and the state-space hidden state ($\boldsymbol{x}_t$) become, respectively:

$$\boldsymbol{y}_t = \begin{bmatrix} y_t^{j_1} \\ \vdots \\ y_t^{j_J} \end{bmatrix}, \quad \boldsymbol{x}_t = \begin{bmatrix} x_t^{j_1} \\ \vdots \\ x_t^{j_J} \end{bmatrix}.$$

This requires a new set of discrete symbols to represent the switching variable $\sigma_t^{\mathbb{D}} \in \mathbb{D} := \{\sigma_1, \sigma_2, .., \sigma_D\}$ among the multidimensional linear state-space model ($A^{\mathbb{D}}(\sigma_t^{\mathbb{D}})$ and $Q^{\mathbb{D}}(\sigma_t^{\mathbb{D}})$).

The set of discrete symbols $\mathbb{D}$ arises from the combination of the scalar symbols from each kinematic variable ($\mathbb{S}^{\mathcal{J}}$), as indicated in Figure 4.1 for the sit-to-stand movement example. A function $\sigma = \varphi(s^{j_1}, ..., s^{j_J})$ maps the combination of all joint angle symbols ($s^{\mathcal{J}}$) to the set $\mathbb{D}$. For instance, in the Sit-to-Stand movement shown in Figure 4.1 $\varphi(s^{j_1}, ..., s^{j_J})$ is a function of the knee and trunk symbols (s^{j_1}, s^{j_2}, respectively). For the example in Figure 9.2, it may be defined as:

$$\varphi(s^{j_1}, s^{j_2}) = \begin{cases} 1, & s^{j_1} = 1, s^{j_2} = 1, \\ 2, & s^{j_1} = 1, s^{j_2} = 2, \\ 3, & s^{j_1} = 2, s^{j_2} = 2, \\ 4, & s^{j_1} = 2, s^{j_2} = 3, \\ 5, & s^{j_1} = 3, s^{j_2} = 1. \end{cases} \tag{4.2}$$

Each movement type ($\tau_i \in \mathcal{T}$) is described by a sequence of symbols σ_t from the set $\mathbb{D}$ and forms the subset $\mathcal{D}_{\tau_i} \subset \mathbb{D}$. The collection of all subsets $\mathcal{D}_{\tau_i}$ forms the family of sets $\mathcal{D}$.

Taking as an example (4.2) and the sit-to-stand movement depicted in Figure 4.1 we can now describe it in terms of σ_t. The sequence

$$\sigma_t = (1, ..., 1, 2, ..., 2, 3, ..., 3, 4, ...4)$$

represents the sit-to-stand movement (τ_1), as shown in Figure 4.1, and the subset $\mathcal{D}_{\tau_1} := \{1, 2, 3, 4\} \subset \mathbb{D}$ contains only the symbols for movement τ_1. A transition from $\sigma_t = 4$ to $\sigma_t = 5$ marks the end of the movement τ_1.

These multidimensional linear state-space models ($A^{\mathbb{D}}(\sigma_t^{\mathbb{D}})$and $Q^{\mathbb{D}}(\sigma_t^{\mathbb{D}})$) are a combination of the scalar linear state-space models defined in (4.1) The model can be written as:

$$\begin{aligned}
\boldsymbol{x}_{t+1} &= \left[\begin{array}{c|c} I^J & \begin{matrix} v(s_t^{j_1}) \\ \vdots \\ v(s_t^{j_J}) \end{matrix} \end{array}\right] \begin{bmatrix} x_t^{j_1} \\ \vdots \\ x_t^{j_J} \\ 1 \end{bmatrix} + \begin{bmatrix} r(s_t^{j_1}) \\ \vdots \\ r(s_t^{j_J}) \end{bmatrix} \\
\boldsymbol{y}_t &= \left[\begin{array}{c|c} I^J & \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} \end{array}\right] \begin{bmatrix} x_t^{j_1} \\ \vdots \\ x_t^{j_J} \\ 1 \end{bmatrix} + \begin{bmatrix} w(s_t^{j_1}) \\ \vdots \\ w(s_t^{j_J}) \end{bmatrix}
\end{aligned} \tag{4.3}$$

where I^J is the identity matrix of size J.

We use this multidimensional representation in two ways: first to determine the start and end of each movement (movement period), second to determine which movement type (τ) was executed. The procedure will be explained in Section 4.3.

4.2 SLDS MODEL PARAMETRIZATION

Now that the parallel between human movement description and Switching Linear Dynamic System (SLDS) modeling has been made, we can explain how to parametrize the SLDS model for our purpose. This parametrization is a supervised learning procedure that uses manually labeled datasets. The importance of having a supervised learning procedure based on manually labeled training datasets is to ensure that the SLDS model represents the formal definitions for movement analysis presented in Section 2.3. Another important aspect is that users with no engineering background can feed the system with movement types and datasets without any knowledge of SDLS or the underlying mathematics.

In this section, we explain how the manual labeling of the training dataset is done. Next we demonstrate how the constant velocity parameters for (4.1) and (4.3) are calculated. Finally we clarify how the transition matrices in (2.5) for the scalar and multidimensional cases are extracted. Figure 9.3 gives an overview of the parametrization explained in this section as well as the segmentation and parameter extraction procedure that will be explained in Section 4.3.

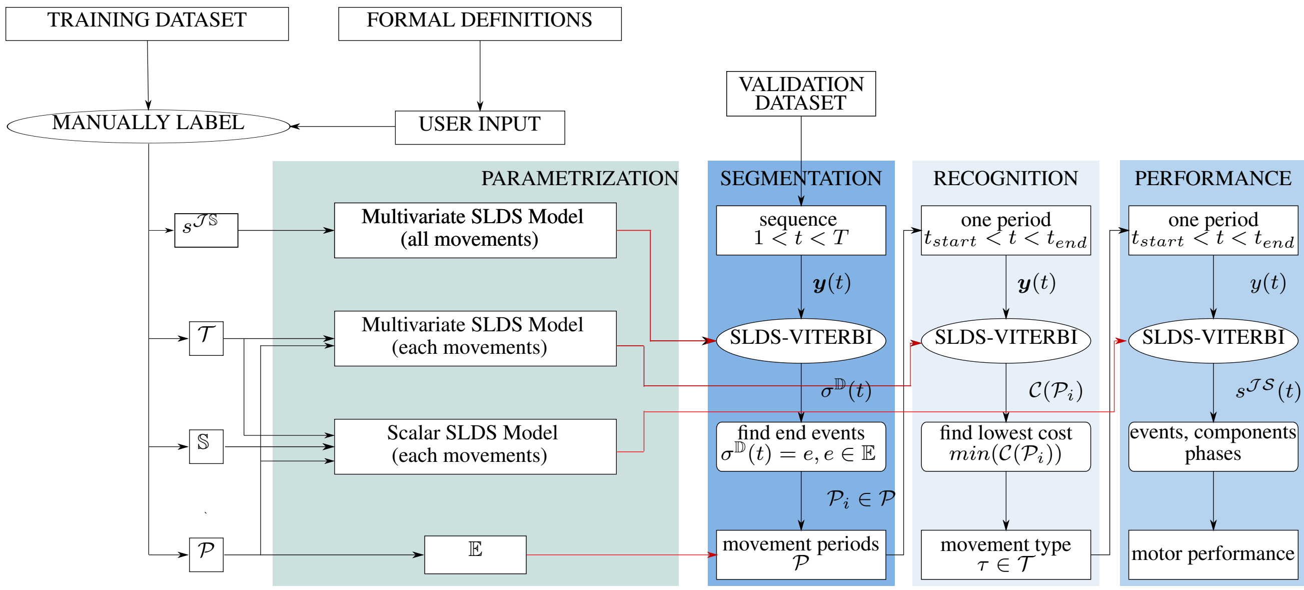


Figure 4.2: Block diagram illustrating the complete method. Particularly, data flow of variables and important algorithms steps for the proposed approach are depicted.

4.2.1 Manually labeling training dataset

The first step for the model parametrization is to manually label the training datasets. Essentially this means annotating the curves as in Figure 9.2 based on the formal definitions from Section 2.3 and marking the movement periods and movement types as in Figure 3.2a.

For each kinematic variable (e.g each joint ($j_i \in \mathcal{J} := \{j_1, ..., j_J\}$) angle) in each training dataset, all events (as defined in Section 2.3) are manually annotated, typically through visual inspection. The corresponding symbol $s_t^{j_i,\mathbb{S}} \in \mathbb{S}^{j_i}$ - as described in Section 4.1.1 - for each interval between two events is also manually provided. All samples in the time-series are then automatically labeled with the corresponding symbol $s_t^{j_i,\mathbb{S}}$, as in Figure 4.1, and the sets of symbols for each joint $\mathbb{S}^{j_i} := \{s^{j_1}, ..., s^{j_J}\}$ is defined.

The time instant marking the boundaries (t_{start} and t_{end}) of each movement - as defined in Section 2.3 - and the movement type (τ_n) within this boundaries are also manually annotated, as in Figure 3.2a. The result is the set of ordered pairs that represent the movement periods $\mathcal{P} := \{(t_{start_1}, t_{end_1}), ..., (t_{start_T}, t_{end_T})\}$ and the set of movement types $\mathcal{T} := \{\tau_1, ..., \tau_N\}$. Combining the information from $\mathbb{S}^{j_i}, \mathcal{P}, \mathcal{T}$ results in the family of sets $\mathcal{S}^{j_i} = \{\mathcal{S}^{j_i}_{\tau_1}, ..., \mathcal{S}^{j_i}_{\tau_N}\}, \mathcal{S}^{j_i}_{\tau_n} \subset \mathbb{S}$ each containing only the symbols $s^{j_i \mathbb{S}}$ associated with movement type τ_i.

The function $\varphi(s^{j_1}, ..., s^{j_J})$ (as (4.2) from Section 4.1.2) is automatically generated with all sets $\mathbb{S}^{j_i}$ and $\mathcal{T}$, as represented in Figure 4.1. Function φ yields the multidimensional SLDS symbols $\sigma_t^{\mathbb{D}}$ and the resulting set of symbols ($\mathbb{D}$). Combining the information from $\mathbb{D}, \mathcal{P}, \mathcal{T}$ results in the family of sets $\mathcal{D} = \{\mathcal{D}_{\tau_1}, ..., \mathcal{D}_{\tau_N}\}, \mathcal{D}_{\tau_n} \subset \mathbb{D}$ each containing only the symbols ${\sigma_t}^{\mathbb{D}}$ associated with movement type τ_i. Finally, the set containing only the symbols associated with the end of each movement forms the set of end symbols $\mathbb{E} := \{\sigma^{\mathbb{D}}_{t_{end},\tau_1},...,\sigma^{\mathbb{D}}_{t_{end},\tau_N}\}$.

It is important to remark that some symbols $s^{j_i,\mathbb{S}} \in \mathbb{S}^{j_i}$ and $\sigma^{\mathbb{D}} \in \mathbb{D}$ are common to different movements. In the example from Figure 4.1, the symbols for the trunk tilt ($s_t^{j_2,\mathbb{S}}$) representing upright static pose ($s_t^{j_2,\mathbb{S}} = 1$), lean forward ($s_t^{j_2,\mathbb{S}} = 2$) and lean backward ($s_t^{j_2,\mathbb{S}} = 3$) are the same for both the sit-to-stand (τ_1) and the stand-to-sit (τ_2) movements.

Now that we have the labeled dataset, the sets of symbols $\mathbb{S}^{j_i}$, $\mathcal{S}^{j_i}$, $\mathbb{D}$ and $\mathcal{D}$, it is possible to automatically calculate the elements of the SDLS model: the constant velocity parameters ($v(s_t^{j_i})$) in (4.1) and Section 4.1.2 (they are the same in both models) to form $A^{\mathcal{J},\mathcal{S}}$,$A^{\mathcal{D}}$ and $A^{\mathbb{D}}$; the covariance matrices $Q^{\mathcal{J},\mathcal{S}}$,$Q^{\mathcal{D}}$ and $Q^{\mathbb{D}}$; and the transition matrices $\Pi^{\mathcal{J},\mathcal{S}}$, $\Pi^{\mathcal{J},\mathbb{S}}$, $\Pi^{\mathbb{D}}$ and $\Pi^{\mathcal{D}}$. Figure 9.3 shows the information flow for each of these elements.

4.2.2 Constant velocity parameters

The constant velocity parameter in (4.1) is estimated as the mean of the instant velocity calculated from every labeled sample in the training dataset matching each symbol ($s_t^{j_i}$). The state noise covariance $Q^{\mathcal{J},\mathcal{S}}(s_t^{j_i,\mathcal{S}})$ is the corresponding covariance matrix. For the multidimensional SLDS, the matrix $Q^{\mathcal{D}}(\sigma_t^{\mathcal{D}})$ is a diagonal matrix with the corresponding elements of $Q^{\mathcal{J},\mathcal{S}}(s_t^{j_i,\mathcal{S}})$.

4.2.3 Transition matrices Π

The state transition coefficients $\Pi(a, b)$ in the transition matrix Π in (2.5) represents the probability of the switching variable assuming each symbol at instant t given its value at $t - 1$. Since a labeled sequence is available, we estimate each transition coefficient as the relative frequency of each transition [48]:

$$\Pi(a,b) = \frac{\sum_{t=2}^{T} \xi_t(a,b)}{\sum_{t=1}^{T} \gamma_t(a)} \tag{4.4}$$

where $\xi_t(a, b) = 1$ indicates a transition $s_{t-1} = a \rightarrow s_t = b$ and $\xi_t(a, b) = 0$ otherwise, and $\gamma_t(a) = 1$ indicates $s_t = a$ and $\gamma_t(a) = 0$ otherwise. In other words: we count how many transitions between the symbols for the switching variables and divide by the number of samples in the labeled sequence. If labeled data sets were not available, estimation techniques, such as the Expectation Maximization algorithm must be employed [43].

For both the scalar and multidimensional SLDS the sequence of symbols $s_t^{\mathcal{J},\mathbb{S}} \in \mathbb{S}^{\mathcal{J}}$ and $\sigma_t^{\mathbb{D}} \in \mathbb{D}$ are given for the entire labeled training datasets. The elements of the transition matrices $\Pi^{\mathcal{J},\mathbb{S}}$ and $\Pi^{\mathbb{D}}$ are calculated using (4.4). The transition matrices $\Pi^{\mathcal{J},\mathbb{S}}$ and $\Pi^{\mathbb{D}}$ contain the coefficients for all possible transitions among all symbols $s_t^{\mathcal{J},\mathbb{S}} \in \mathbb{S}^{\mathcal{J}}$ and $\sigma_t^{\mathbb{D}} \in \mathbb{D}$ respectively.

In the segmentation task $\Pi^{\mathbb{D}}$ is used (along with $A^{\mathbb{D}}, Q^{\mathbb{D}}$ and $\mathbb{E}$) to detect the boundaries of each movement in a movement sequence, as indicated in Figure 9.3.

To analyze each movement separately in the movement type recognition task, we only need the transition coefficients associated with each symbol in each movement type subset ($\mathcal{D}_{\tau_n} \subset \mathbb{D}$). A new transition matrix $\Pi^{\mathcal{D}_{\tau_n}}$ is automatically formed only with these coefficients. For example, if $\mathbb{D} := \{1, 2, 3, 4\}$ and $\mathcal{D}_{\tau_1} := \{1, 3\}$ we have the following $\Pi^{\mathbb{D}}$:

$$\Pi^{\mathbb{D}} = \begin{bmatrix} \Pi^{\mathbb{D}}_{1,1} & \dots & \Pi^{\mathbb{D}}_{1,4} \\ \vdots & \ddots & \vdots \\ \Pi^{\mathbb{D}}_{4,1} & \dots & \Pi^{\mathbb{D}}_{4,4} \end{bmatrix}$$

and the following $\Pi^{\mathcal{D}_{\tau_1}}$:

$$\Pi^{\mathcal{D}_{\tau_1}}_{1,1} = \begin{bmatrix} \Pi^{\mathbb{D}}_{1,1} & \Pi^{\mathbb{D}}_{1,3} \\ \Pi^{\mathbb{D}}_{3,1} & \Pi^{\mathbb{D}}_{3,3} \end{bmatrix}$$

.

For the motor parameter extraction task, only the transition coefficients from $\Pi^{\mathcal{J},\mathcal{S}}$ corresponding to each $s^{\mathcal{J},\mathcal{S}} \in \mathcal{S}^{\mathcal{J}}$ are necessary. The inverse function φ^{-1} in (4.2) is used to map the symbols in each $\mathcal{D}_{\tau_n} \rightarrow \mathcal{S}^{\mathcal{J}}_{\tau_n}$ and a new set of transition matrices $\Pi^{\mathcal{J},\mathcal{S}_{\tau_n}}$ are automatically formed for each movement type (τ_n) and joint (j_i).

4.3 SEGMENTATION AND MOTOR PERFORMANCE PARAMETERS EXTRACTION

Now that we have all the elements and parameters of the SLDS representing the movements in the training dataset, it is possible to use this model to automatically execute the segmentation, movement type recognition and motor performance extraction tasks in new dataset. The main steps of the procedure to execute these tasks are shown in Figure 9.3.

4.3.1 Segmentation

The segmentation task begins with the estimation of the sequence of symbols $\sigma_t^{\mathbb{D}} \in \mathbb{D}, 1 < t < T$ that best describes the multidimensional time-series of the sequence of movements. To achieve this, we run the SLDS-Viterbi algorithm from [44] with the multidimensional SLDS model $(A^{\mathbb{D}}, Q^{\mathbb{D}}, \Pi^{\mathbb{D}})$ that represents the complete set $\mathbb{D}$.

Next the algorithm finds the boundaries of each movement searching for the last element in the repetitive sequence of symbols $\sigma_t^{\mathbb{D}} \in \mathbb{E}$ that represent the end of each movement type. In the example Figure 4.1 this would mean finding the last symbol $\sigma_t = 4$ at t_5 to mark the end of the sit-to-stand and the begin of another movement. The result of the segmentation is the set of movement periods $\mathcal{P} := \{(t_{start_1}, t_{end_1}), ..., (t_{start_T}, t_{end_T})\}$.

To find the phase boundaries the same procedure can be used, changing only the set of symbols that mark the end of each phase, instead of each movement. In the experiments presented in Chapters 6 and 7 only the complete movement will be considered for segmentation, to limit extension of the experiments.

4.3.2 Movement type recognition

For the movement type recognition task the approximate SLDS-Viterbi algorithm is used again in each period (t_{start}, t_{end}) of the previously segmented movement. However, this time using the multidimensional SLDS models that represent each movement separately $(A^{\mathcal{D}}, Q^{\mathcal{D}}, \Pi^{\mathcal{D}})$. The SLDS-Viterbi runs for each SLDS model $(A^{\mathcal{D}\tau_n}, Q^{\mathcal{D}\tau_n}, \Pi^{\mathcal{D}\tau_n})$ for each movement type (τ_n) and the resulting cost function $\mathcal{C}(y_t, \mathcal{D}_{\tau_n}), t_{start} < t < t_{end}$ is used to determine which movement type was executed. The multidimensional SDLS model for the movement (τ_n) that yields the lowest cost in the SLDS-Viterbi algorithm labels the segmented movement.

In the example in Figure 4.1 this would mean running the SLDS-Viterbi only in the interval $[t_0, t_5]$. A successful result is when the SLDS model $(A^{\mathcal{D}\tau_n}, Q^{\mathcal{D}\tau_n}, \Pi^{\mathcal{D}\tau_n})$ for $\mathcal{D}_{\tau_1}, \tau_1 = 1$ results in the lowest overall cost correctly recognizing the movement type (where $\tau_i = 1$ represents Sit-to-Stand, for example).

4.3.3 Motor parameter extraction

Once each movement is segmented and the movement type is indicated, it is possible to analyze each execution and extract the motor performance parameters. In this case, each kinematic variable is estimated separately with the scalar SDLS models $(A^{\mathcal{J},\mathcal{S}}, Q^{\mathcal{J},\mathcal{S}}, \Pi^{\mathcal{J},\mathcal{S}})$.

The SLDS-Viterbi algorithm estimates the best sequence $s_t^{\mathcal{J},\mathcal{S}}$ for each kinematic variable (i.e. joint (j_i) angle). The intervals of repetitive sequence of switching variables values represent the components (c) as defined in Section 2.3. A change in the value of the switching variable represents an event (e).

It is now possible to describe each movement in terms of events, components and phases, according to the formal definition presented in Section 2.3 and to extract the motor performance parameters.

In the sit-to-stand example in Figure 4.1 a successful result would be to estimate the sequence $s_t^{j_1} = (1, .., 1, 2, ..., 2, 3, ..., 3, 4, ...4)$ in the interval $[t_1, t_5]$ and indicate the events and phases. With this representation the relevant motor performance parameters - such as the ones shown in Figure 3.2b - can be directly extracted.

5 UNIVARIATE MOVEMENT CYCLE DIAGRAM

5.1 EXPERIMENTS

The aim of this experiment is to automatically obtain a movement cycle diagram for the Sit-Stand-Sit movement using only one variable, the knee angle.

Knee extension (and flexion) initiation and period are spatiotemporal features of the Sit-Stand-Sit movement. In [30], for instance, a baseline of descriptive data is established for a group of healthy adults for this movement. Significant differences are found in the initiation and period of knee extension comparing the mean data from young male subjects and elderly female subjects. This is one example of the variability in the execution of the same movement by different populations.

To showcase the advantages of the SLDS approach over heuristic approaches [11, 49], we obtained the movement cycle diagram using the SLDS approach and compared it to an approach based on heuristics and thresholding based classification: the Finite State Machine (FSM). The SLDS approach used was the univariate SLDS presented in Section 4.1.1. For simplicity, we considered the Sit-to-Stand-to-Sit as one movement, so the problem is reduced to only detecting events. Segmentation and Movement Type Identification is not dealt with in this case. This simplification is necessary for direct comparison with FSM, that lacks the capability of executing the Segmentation and Movement Type Identification tasks.

The SLDS model was obtained following the procedure presented in Section 4.2 and the dataset graphically presented in Figure 5.1. The training dataset was manually labeled indicating the events and components of the Sit-Stand-Sit movement. Red vertical lines in Figure 5.1 represent the events that bound the four components: Sit (c_1), Knee Extension (c_2), Stand (c_3) and Knee Flexion (c_4).

For comparison, we developed a model using a FSM model with thresholds based on the instant velocity of the knee displacement. A FSM is a mathematical model to represent sequential logic [50]. The model is composed of a finite number of discrete states $S := \{s_1, \ldots, s_S\}$, as in the HMM model. At each instant the machine can be in only one state $s_t \in S$. An event sets the transition from one state to another. The difference from an FSM to HMM model is that in the FSM model the transition is triggered by a fixed logic condition and in the HMM model there is a probability of transition. Similarly, the transitions in the discrete states in the SLDS model are also probabilities.

In the FSM model the states are the same as in the SLDS model and represent the compo-

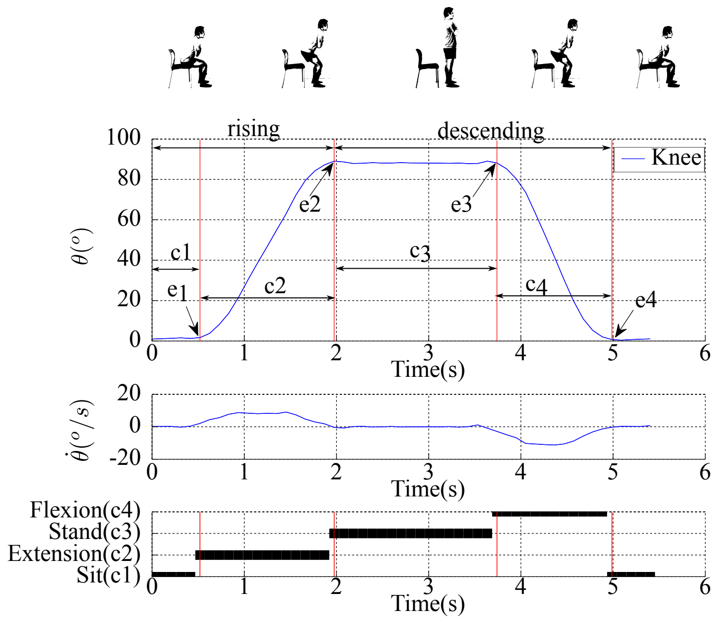


Figure 5.1: Training data set consisting of one execution of the Sit-Stand-Sit movement cycle. Events (e_i), components (c_i) and the rising and descending phases are identified using black arrows and red vertical lines. θ and $\dot{\theta}$ indicates angle and angular velocity.

nents: Sit (c_1), Knee Extension (c_2), Stand (c_3) and Knee Flexion (c_4). The simplest approach to set the logic condition for transitions would be to set the threshold to zero during the sit and stand component, positive velocity for the knee extension component and negative velocity of the knee flexion.

However, looking closely to the instantaneous velocity from the training dataset, shown in Figure 5.1, we see that these values are not suitable because the velocity is not constant at zero during Sit and Stand. Also, between Stand (c_3) and Knee Flexion (c_4), at $3,6s$, there is a positive overshoot in the knee angular velocity before it becomes negative. These conditions can be due to noise in the sensor or short transient movements which are captured by the sensors. Therefore, the logical conditions to transition to and from the Sit (c_1) and Stand (c_4) components are, respectively, the maximum and minimum angular velocity in each component.

As we will show in the results section (Section 5.3), these thresholds are extremely dependent on the sample dataset used for modeling. Other heuristic approaches can be used to extract a different model, but again they will be dependent on the dataset used for modeling and the variable in question [5]. Finally, it is important to observe that the movement cycle diagram in Figure 5.1 should be the same whether obtained by SLDS model, FSM or manually.

5.2 SETUP AND PROTOCOL

The database for this experiment, was recorded using a set of 2 three-axis accelerometers from Delsys Trigno Wireless System [3]. The sensors were placed in the right shank and thigh aligned with the frontal plane in the standard cardinal plane for human motion [1]. Each accelerometer reading was first calibrated to remove offset in each axis and the effects of the sensor's non-linear sensitivity using a least squares approach [51]. Next each accelerometer reading was decimated to 30 Hz sampling frequency and smoothed by a low-pass filter (moving average filter, window size 5 samples). The angular position of each sensor was estimated using the tri-axis tilt sensing procedure [51]. Combining the two absolute angle estimates with a 1-DOF biomechanical model for sagittal plane knee flexion/extension, the absolute angle for the knee joint was calculated.

The database recorded consists of measurements from one healthy subject in six scenarios: a single execution of the Sit-Stand-Sit movement executed with three different velocities, resulting in a "fast", "normal" and "slow" movement; a sequence of 5 consecutive Sit-Stand-Sit, in which the subject was instructed to execute the knee extension and knee flexion at his self-selected velocity; and a sequence of 5 consecutive Sit-Stand-Sit movements in which the subject was instructed to execute each repetition at a randomly different velocity.

The database for this experiment was obtained in Montpellier, France and according to the context, there was no requirement for approval in the Research Ethics Committee.

5.3 RESULTS

In this section we will closely analyze the capability to correctly detect events and generate the movement cycle diagram. The results for the movement cycle diagram for one repetition, executed at different velocities is shown in Figure 5.2. For the first case, the "fast" execution, both approaches had similar results. In fact, the finite state machine (FSM)/threshold approach was more accurate in detecting the transitions, matching the ground truth at $t = 0.10s$ (transition $c_1 \rightarrow c_2$) and at $t = 1.14$ (transition $c_2 \rightarrow c_3$). The SLDS model correctly estimated the sequence of components, with a delay of one sample in the events $c_2 \rightarrow c_3$ and $c_3 \rightarrow c_4$.

In the second case, the "normal" velocity execution (which is similar to the training data), the performance of the FSM/threshold approach is poor. It estimates early $c_1 \rightarrow c_2$ (at $t = 0.31s$). The transition $c_2 \rightarrow c_3$ is correctly estimated. But during component c_3 there is an incorrect estimation of $c_3 \rightarrow c_4$, at $t = 3.12s$, which leads to the sequence of transitions

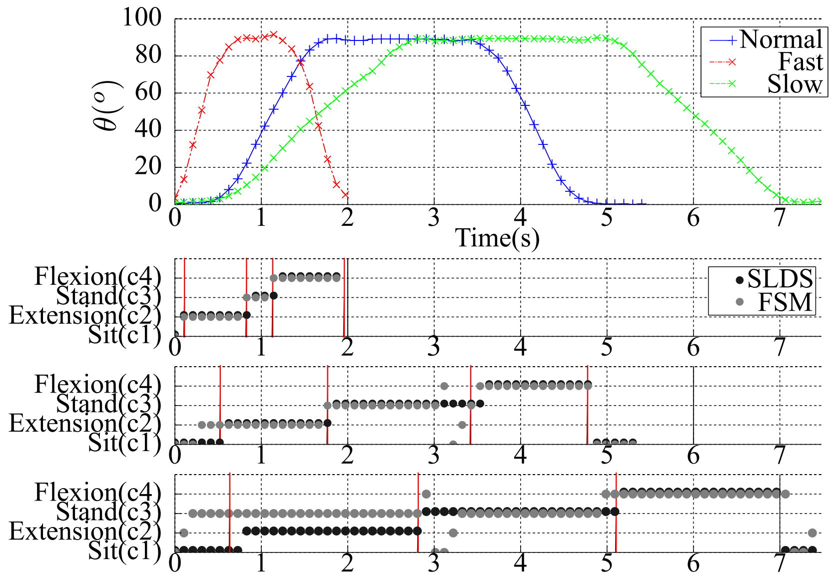


Figure 5.2: Movement cycle extraction validation with the Switching Linear Dynamic System (SLDS) model and the Finite State Machine with thresholds (FSM) model using datasets containing one movement execution with different velocities: Normal, Fast and Slow. Red vertical lines represent the beginning of each component in the hand segmented dataset (used as ground truth).

$c_4 \rightarrow c_1 \rightarrow c_2 \rightarrow c_3$, anticipating the correct $c_3 \rightarrow c_4$ transition at $t = 3.53s$. Again the SLDS approach estimated the events with one sample delay and correctly maintained the estimation throughout the component.

Finally, in the "slow" execution the FSM/threshold approach estimated the $c_1 \rightarrow c_2$ transition very early on, at $t = 0.10s$. It then lead immediately to the estimation of transition $c_2 \rightarrow c_3$, and remained on c_3 until $t = 2.80s$, when it estimated $c_3 \rightarrow c_4$ at $t = 2.91$. It then lead to a sequence of transitions $c_4 \rightarrow c_1 \rightarrow c_2 \rightarrow c_3$, returning to the correct component. The SLDS approach correctly estimated the sequence of events, with two samples delay in the transition detection at $t = 0.83s$, and one sample delay at $t = 2.91s$ and $t = 5.19s$.

In the 5 times Sit-Stand-Sit with "normal" velocity, presented in Figure 5.3, the FSM/ Threshold approach exhibited the same misclassification issues seen on the cross validation with one repetition. Missed estimation of the transitions lead to a sequence of transitions before returning to the correct estimation at $t = 3.43s$ and at $t = 16.72s$. Again a premature estimation $c_1 \rightarrow c_2$, at $t = 23.50s$ lead to an incorrect estimation of $c_2 \rightarrow c_3$ at which the estimation is locked until it transits to another full cycle through the sequence $c_3 \rightarrow c_4 \rightarrow c_1 \rightarrow c_2 \rightarrow c_3$, at $t = 25.69s$ and returns to the correct estimation path. The SLDS approach correctly estimated the sequence of events and had minor delays in the transition detections.

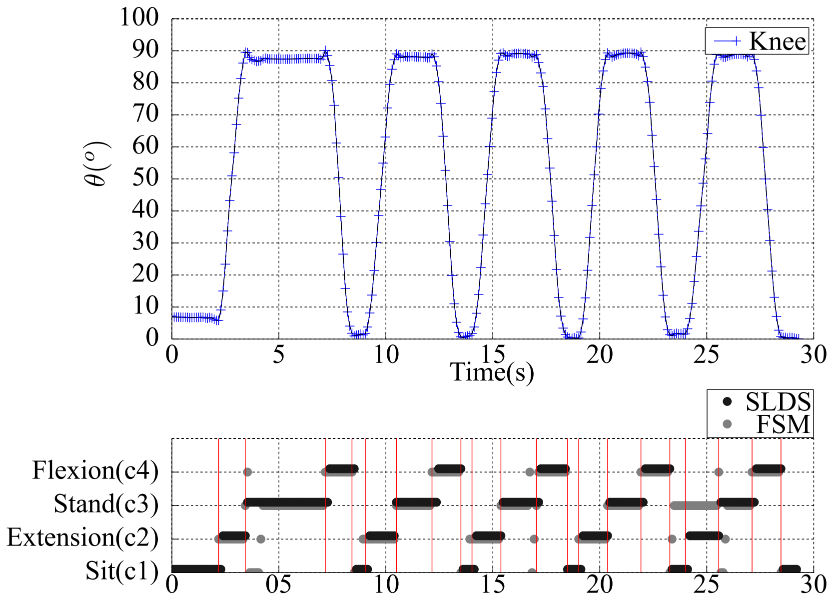


Figure 5.3: Cross validation for the movement cycle extraction with the Switching Linear Dynamic System (SLDS) model and the Finite State Machine with thresholds (FSM) model using datasets containing a sequence of 5 Sit-Stand-Sit movements executed with normal velocity. Red vertical lines represent the beginning of each component in the hand segmented dataset (used as ground truth).

Figure 5.4 shows the last experiment, the 5 times Sit-Stand-Sit with varied velocity. The same issues for the FSM/ Threshold approach can be noticed again in this test: at $t = 9.15s$ and at $t = 11.02s$. The SLDS again correctly estimated the sequence of components, with some delay in the transition detection. Particularly at $t = 15.08s$, the SLDS was able to detect a $c_4 \rightarrow c_2$ transition. In this case, since it is just a valley point, there was no consecutive samples at the "Sit" (or component c_1). The FSM/Threshold had to go through component c_1, in order to reach the correct estimation of c_2.

5.4 DISCUSSION

We showed that the modeling of the Sit-Stand-Sit motion converting the standard definitions into elements of the SLDS model results in an effective model to segment and extract spatiotemporal features, and generate the movement cycle diagram. The results support that our approach is a straight-forward modeling procedure, requires a small training dataset and is suited for classifying and segmenting the components of a movement. Besides, the results obtained with the SLDS model are superior to FMS / Threshold approach.

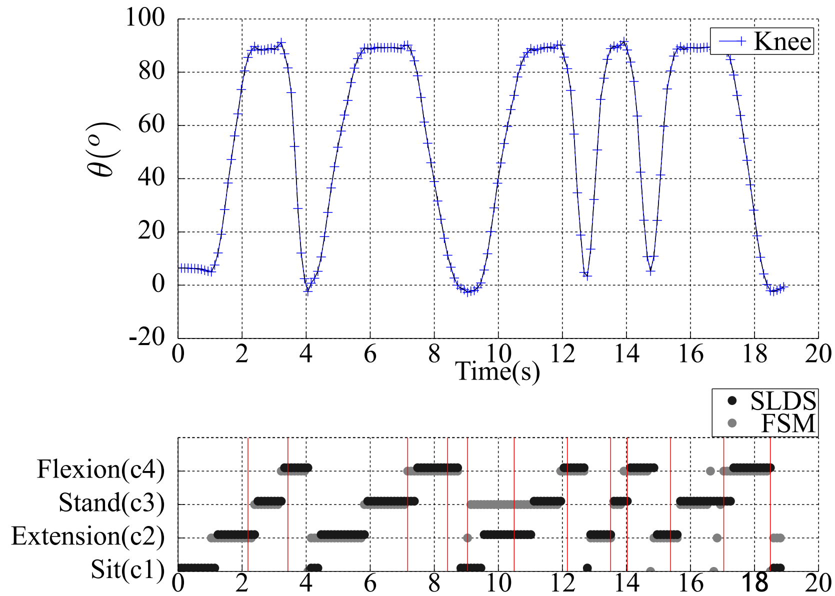


Figure 5.4: Cross validation for the movement cycle extraction with the Switching Linear Dynamic System(SLDS) model and the Finite State Machine with thresholds (FSM) model using datasets containing a sequence of 5 Sit-Stand-Sit movements executed with varied velocity. Red vertical lines represent the beginning of each component in the hand segmented dataset (used as ground truth).

As mentioned in 5.1, knee extension and flexion period are well stablished descriptive spatiotemporal features of the Sit-Stand-Sit movement executed by healthy adults. In our database, the knee extension period in the "fast" execution correspond to the baseline data for healthy young male adults while the knee extension period in the "slow" execution corresponds to the baseline data for healthy elderly female subjects.

The results presented in this chapter shifts from the heuristics based or custom build algorithms which are strongly dependent on the dataset or the movement studied. Since we strongly based our approach on the standard definitions of the movement, the information extracted can readily be compared to standardized results for healthy and impaired subjects such as shown in [30, 18].

6 MULTIVARIATE SEGMENTATION AND MOTOR PERFORMANCE PARAMETERS EXTRACTION

6.1 EXPERIMENTS

The intent of this study is twofold. First to show that our proposed framework is capable of executing the following three tasks: segmentation, movement type identification and motor performance parameters extraction based on measurements from a sequence of movements. Second to show the flexibility for using general SLDS models for different subjects.

The performance of the multivariate SLDS model was tested separately for each task: segmentation, movement type recognition and motor performance parameters extraction. For all tasks the parametrization procedure shown in Figure 9.3 was carried out in advance with training data set. To avoid carrying over errors, in each validation task the true data set (based on manual labeling) was used. This means the movement type recognition was validated with correctly segmented data set and the motor parameter extraction was validated with the correct movement type model.

For each subject two different validation scenarios were executed: intrasubject and inter-subject. The intrasubject SLDS model was parametrized using two data sets from the same subject and the third data set was used for validation. The inter-subject model was parametrized using a leave-one-out validation analysis: first the SLDS model was parametrized using one data set from each subject except one. The data set not used for parametrization was then used for validation.

All three tasks were tested using the intrasubject and inter-subject data set for both the 5STS and MWB data set.

To validate the Motor Performance Parameters Extraction aspect of the proposed approach we focused on three parameters for the Sit-to-Stand movement. This movement contains many aspects interesting to highlight the versatility of the proposed method, as opposed to heuristic and parameter-specific approaches. The three parameters are:

- **Peak trunk tilt** shows the capability for peak detection. The peak trunk tilt is marked in Figure 3.2b and correspond to event (e_4) in Figure 9.2.
- **Maximum knee angular velocity at knee extension**. To determine this parameter we must first detect the boundaries of the knee extension component which includes the transition from a static position to the extension. The boundaries for the knee extension

component are marked in Figure 3.2b and correspond to events (e_2,e_5) in Figure 9.2. The peak knee angular velocity is calculated within this interval.

- **Rising phase period** as shown in Figure 3.2b. The rising phase period is bounded by events (e_1,e_5) from two different kinematic variable, shown in Figure 9.2.

These parameters are spatiotemporal features of the Sit-to-Stand movement that have baseline values recorded in the literature for different populations [30, 22, 23].

In the validation of all three tasks the manually labeled data sets were used as ground truth to test the results estimated by each step in the proposed approach. To quantify the performance of the proposed approach for the segmentation and feature extraction tasks we used three metrics: sensitivity, false positive and false negative rates [52]. A correct transition detection (or true positive) was declared if the algorithm estimated the correct transition within an time interval of a determined time error tolerance t_{error}. The tolerance t_{error} corresponds to the time difference between the ground truth time of a given transition and the estimated moment of the same transition. Therefore, if the transition is estimated within a delay or advance smaller than t_{error}, it is still considered correct. Other works, [33, 34], have employed similar measures. A false negative is declared for each missed transition by the algorithm and a false positive is the estimation of a transition when there is none. Sensitivity is the ratio between true positives and true positives plus false negatives. In Section 6.3.1 the sensitivity, false negative and false positive rates are presented as percentage rates.

In the movement type recognition task each movement was declared correct if it matched the hand labeled data set. The results in Section 6.3.1 are presented as percentage rates of correctly estimated movement type over the total number of movements in all validation experiments.

The estimation for motor performance parameters relies on the detection of the moment that each event occur. Events precisely detected yields correct estimation of the parameter. A delay in the estimation results in an estimation error.

6.2 SETUP AND PROTOCOL

The data set for the multivariate experiments, were recorded using a set of 7 three-axis accelerometers from Delsys Trigno Wireless System [3]. The sensors were placed in the right and left shank and thigh, neck and right and left upper arm, all aligned with the frontal plane in the standard cardinal plane for human motion [1]. Each accelerometer reading was first calibrated to remove offset in each axis and the effects of the sensor's non-linear sensitivity using a least squares approach [51]. Next each accelerometer reading was decimated to 30 Hz sampling frequency and smoothed by a low-pass filter. The angular position of each sensor was estimated using the tri-axis tilt sensing procedure [51]. Combining two absolute angle estimates with a 4-DOF biomechanical model of the human body, 2-DOF for sagittal plane (knee and hip flexion/extension) and 2-DOF for the frontal plane (each arm lateral abduction/adduction), the absolute angle for each body joint of interest was calculated.

Six healthy subjects (ages 27-45, four male, two female) were recruited to perform sequences of whole body movements after providing informed consent. Each subject performed two different sets of movement: 5 Times Sit-to-Stand (5STS) and Mixed Whole Body Movements (MWB), which included one execution of each of the following movements: sit-to-stand, both arms lateral 90^o raise, squat, hip flexion while standing (bow) and stand-to-sit. The 5STS was chosen because it is a widely used performance test in clinical practice. The movements for the MWB data set were chosen as combination of exercises that use different body parts. Each subject performed three times each of the two types of movement sequences resulting in six different data set per subject.

The database for this experiment was obtained in Montpellier, France and according to the context, there was no requirement for approval in the Research Ethics Committee.

6.3 RESULTS

6.3.1 Segmentation and Movement Type Identification

The results for the validation experiments for the segmentation and movement type recognition tasks are presented in Table 6.1. An example result of segmentation by this method can be found in Figure 3.2a for a Mixed Whole Body Movement (MWB) data set.

There is a clear increase in the success rate for the segmentation task related to the time error bound. In validation cases all transitions indicating the end of each movement, as explained in Section 4.3, were successfully detected within the error bound $t_{error} < 0.3s$. In the 5STS there where no false negatives (FN) or false positives (FP), which means the number of estimated transitions matched the number of true transitions. False negatives and false positives appear in the MWB validation. In this case there is a greater variety in the motion types and more variables being tracked which leads to more possible transitions. Finally the MWB inter-subject validation had a better performance than the intrasubject.

For the 5STS data sets all motions were correctly recognized both in the intrasubject and inter-subject validation experiments, which is represented by the correct movement type recognition rate (MT). In the case of the MWB data set the performance in the intrasubject validation experiment was worse than in the inter-subject validation.

Table 6.1: Segmentation Results for the 5 times Sit-to-Stand(5STS) and Mixed Whole Body Movements (MWB) data sets in intra and inter-subject validation. Results are presented as a percentage (%) of correct movement type recognition (MT), correct transition detection(C), false negatives (FN) and false positives (FP), within an error bound (t_{error})

			t_{error}<0.1s			t_{error}<0.2s			t_{error}<0.3s		
data set	Cross-val.	MT	C	FN	FP	C	FN	FP	C	FN	FP
5STS	Intra	100	74	26	0	91	9	0	100	0	0
	Inter	100	72	26	0	85	15	0	100	0	0
MWB	Intra	73	79	28	2	87	22	2	96	13	2
	Inter	97	79	32	0	96	15	0	100	11	0

6.3.2 Motor Performance Parameters Extraction

Motor performance parameter extraction is carried out first describing each movement in terms of events and phases, as shown in Figure 4.1. The instant of determined events and duration of certain phases represent the motor performance parameters, as explained in Section 6.1.

Table 6.2 shows the results of the proposed approach for the motor performance parameters extraction. The mean and standard deviation values for each motor performance parameter for each subject is given. Estimation errors occur in case there is a delay in the event detection. And in this case, the mean and standard deviation for the error for the estimated motor performance parameters are presented. Otherwise there is no estimation error.

6.4 DISCUSSION

Within this study involving the multivariate case the multivariate case, we showcase our framework's ability for segmentation, movement type recognition and motor performance parameter extraction. Movements are modeled as a SLDS according to methodical description from human movement analysis and the procedure for parametrization of the SLDS model avoids the use of heuristics or ad hoc modeling as previous works [45, 33, 34]. The validation results from this experiment confirm that SLDS model is suitable to segment and extract motor performance parameters in a sequence of movements.

Table 6.2: Motor Performance Parameters Extraction results for the proposed algorithm. Three parameters (maximum knee angular velocity, peak trunk tilt and rising phase duration) relevant to the Sit-to-Stand movement are extracted for each subject both using a intrasubject and inter-subject model validation. The mean and std for each parameter are presented, as well as the estimation mean error and std in percentage.

		Max Knee Angular Velocity			Peak Trunk Tilt			Rising Phase Duration		
		mean(std)[rad/s]	Delay in event detection	mean est. error (std)[%]	mean(std)[rad]	Delay in event detection	mean est. error (std)[%]	mean(std)[s]	Delay in event detection	mean est. error (std)[%]
Subject1	Intra	3.598(±0.846)	No	0(±0)	0.774(±0.024)	No	0(±0)	0.492(±0.107)	Yes	5.82(±0.41)
	Inter	-	No	0(±0)	-	Yes	1.59(±3.18)	-	Yes	7.10(±1.94)
Subject2	Intra	2.696(±0.399)	No	0(±0)	0.877(±0.016)	No	0(±0)	0.525(±0.152)	Yes	5.49(±0.30)
	Inter	-	No	0(±0)		Yes	2.04(±4.07)	-	Yes	6.95(±2.78)
Subject3	Intra	2.334(±0.704)	No	0(±0)	0.778(±0.051)	No	0(±0)	0.450(±0.129)	Yes	6.39(±0.56)
	Inter	-	No	0(±0)		No	0(±0)	-	Yes	8.05(±3.01)
Subject4	Intra	2.785(±0.183)	No	0(±0)	0.616(±0.104)	No	0(±0)	0.475(±0.042)	Yes	6.60(±0.64)
	Inter	-	No	0(±0)		Yes	0.76(±1.52)	-	Yes	7.06(±0.60)
Subject5	Intra	1.858(±0.173)	No	0(±0)	0.839(±0.037)	No	0(±0)	0.533(±0.156)	Yes	5.08(±0.34)
	Inter	-	No	0(±0)		Yes	3.54(±7.07)	-	Yes	6.87(±2.83)
Subject6	Intra	3.987(±0.236)	No	0(±0)	1.034(±0.046)	Yes	0(±0)	0.542(±0.017)	Yes	6.16(±0.18)
	Inter	-	No	0(±0)		Yes	0.66(±1.32)	-	Yes	6.16(±0.18)

6.4.1 Segmentation and Movement Type Recognition

Both intrasubject and inter-subject validation results in the segmentation and movement type recognition experiments are comparable to results from previous studies. The results for the segmentation task is comparable to the results reported [33] and [34]. An important remark is that the techniques presented in these two works are implemented online while for this experiment our technique was executed offline. Online implementation of our method is explored n Chapter 7.

The approach presented in [34] combines statistical classifiers and a motion signature function to model each movement and segment a sequence of movements. The whole process involves different standard techniques and some heuristics. Besides, there are some parameters to be tuned. As for the performance, [34] reported a segmentation success rate of 88% within an error bound, which is referred to as compromise interval, but its value is not specified.

On another approach, presented in [33], similar variables, movement types and performance metrics as our study are used. The segmentation was carried out with an online algorithm based on ZVC and HMM. ZVC is very sensitive and leads to over-segmentation therefore some heuristics is used to reject small peaks in short intervals. This work also presents comparisons with a combined ZVC and DTW algorithm. Both HMM and DTW based algorithms perform similarly (accuracy of 91% and 89% respectively in the best case).

Compared with the results for a sequence of sit-to-stand-to-sit movements, reported in [33], our approach performed better for the intrasubject and inter-subject cross validation. In the intrasubject case our approach correctly detected the transitions in 91% of the cases within the error bound of $t_{error} < 0.2s$ and 100% within the error bound of $t_{error} < 0.3s$,compared to 52% and 77% from [33] respectively. The rates of false positives and false negatives were also superior in our experiment. For the error bound $t_{error} < 0.2s$ our results were 9% false negative and 0% false positives compared to 34% and 7% respectively. For the error bound $t_{error} < 0.3s$ there was no false positives or negatives in our results compared to 18% and 2% from [33] respectively.

For a data set containing random mixed motions sequence, [33] reported a success rate of 83% for $t_{error} < 0.2$ and 90% for $t_{error} < 0.3$, his experiment contained more movement types and were captured with a more precise motion capture system, but can be used as reference for adequate success rate. In a similar scenario, we obtained success rate of 96% for $t_{error} < 0.2$ and 100% for $t_{error} < 0.3$. In both studies, ours and [33], delays in the detection of segmentation point are observed and is directly related to the t_{error} tolerance. However, it is possible to achieve high success rates within a relative low error bound, usually shorter that 10% of the average period of each movement type.

For the movement type recognition task we can again compare our results to the ones reported in [33]. In the sequence of sit-to-stand-to-sit movements both studies had a success rate of 100% in the intrasubject and inter-subject validation. For a data set containing random mixed movements sequence, [33] reported a success rate of up to 95% for the intrasubject cross validation and there was no inter-subject validation. This result is significantly higher than our result for the intrasubject validation and similar to our result for the inter-subject validation. The reason for the lower performance in the intrasubject validation of our approach is the reduced data representing each movement. Two data set containing only one example of each movement were used to parametrize the SLDS model in the intrasubject validation as opposed to using five data sets with one example of each movement used to parametrize the SLDS model in the inter-subject validation. This indeed highlights the fact that the SLDS model is improved with more training data sets, even from different subjects.

6.4.2 Motor Performance Parameters Extraction

In the motor parameter extraction task the only similar work is [45]. However the focus is on parameter extraction for each part of the Timed Up and Go (TUG) test, which includes the Sit-to-Stand movement. Relevant motor control parameters were extracted with a mathematical function specifically designed for each movement type and sensor used, so it is expected that the estimation correctly matches the true measured values.

We selected the three motor performance parameters: rising phase duration, peak trunk tilt, and maximum knee velocity, because they were used in other clinical studies to assess the sit-to-stand movement. The results highlight the importance of using a standard movement description as presented in Section 2.3 to extract quantitative information and compare across different previous studies. These parameters are important because they may indicate deviations to baseline values due to impairment. For example, peak trunk tilt is related to compensatory strategies associated to obesity [23] and to hemiplegia [22]. The maximum knee extension velocity was used by [25] to quantitatively monitor the functional recovery of patients after total knee arthroplasty (TKA) as opposed to traditionally used questionnaires. Rising phase duration is one of the most important aspects of the Sit-to-Stand movement regarding the subject's fitness [22, 5].

Our proposed approach was able to successfully extract the motor performance control parameters with a reasonable error margin, as shown in Table 6.2. In the worst case, the estimation of the duration of the rising phase, the maximum average estimation error was 7.10%. For the peak trunk tilt, the worst result was an average estimation error of 3.54%

with a standard deviation of 7.07%. The errors in the estimation of this parameter occurred in the inter-subject cross validation, which means the SLDS model was parametrized with data sets from other subjects. In the intrasubject validation there was no estimation error, which means the moment of the corresponding event was precisely detected. The best case was the estimation of the peak angular velocity with no estimation errors. This is explained by the fact that this parameter is calculated within the interval of a component and does not occurs at its boundaries, so delays in the estimation of its bounding events have no impact in the estimation of this motor performance parameter.

Even though our database was obtained from a group of healthy individuals, there was variability in the peak trunk tilt and maximum knee angular velocity. This is expected when dealing with motor performance parameter extraction from human movement data. Our proposed approach handled this variability keeping estimation errors under 10%, which can be considered an acceptable performance, specially considering the inter-subject validation and also the limited size of training datasets.

6.4.3 Further Discussion

This section presents remarks on the overall performance and application of the proposed method (multivariate SLDS).

One possible concern is the applicability of this method in case the patient has limited mobility and present some difficulties in executing the movement. This issue is illustrated in Chapter 8, but some general comments regarding the applicability of our method are suited here.

Recalling that the proposed method solves two tasks (segmentation and motor performance parameter extraction) the first concern is if the system is able to segment and identify the movement correctly. This is a typical concern in pattern classification problems: it depends on the number of possible classes in the classifier. Furthermore, it also depends on the similarities among the different classes. For example, movements such as sit-stand and squat are similar, while movements such as lateral arm raise and bow are distinct. Finally, we define a movement type based on a certain pattern. Although we are using probabilistic approaches that accommodate variability between the movements in the training data set and movements to be classified, some similarity is required for correct classification. Since we are not dealing with deterministic or algebraic methods, there is no guarantee regarding the threshold for correct classification.

In a clinical application, for patients with mobility restriction, we show in Chapter 8 that our proposed approach works if the patient can execute the movement pattern. Variability in peak values, duration of each phase and velocities are well handed by the algorithm, as proved by the experimental results from this chapter.

Some patients, for example recovering from a stroke, execute the sit-to-stand movement with reduced smoothness. In this case the algorithm can handle the reduced smoothness as long as the slope of the time-series in each interval has the same signal (either positive, negative or neutral).

An important remark is that the constant velocity model is considered in each time interval [t,t+1], not in the whole component interval. As in random variable models, the constant velocity is a random variable, with a mean and a variance. In the Kalman Filter, at each time interval [t,t+1] there is a prediction and update step. In our framework, there is no need for the constant velocity model to be accurate, it is sufficient to provide a better estimate than the constant velocity models for the other components because we are interested in the best sequence of s_t to describe the data set.

Another concern that may arise is the case of multiple attempts, start over, or pause several times during a movement execution.

The sequence of events for each movement type is actually defined according to well established descriptions in the movement analysis literature, such as [2, 20]. Our method is a proposition to transform these descriptions into mathematical models. This is an issue from movement analysis. The description of the movement allows researchers to compare different executions of the same movement. If the movement executed diverges from the description in the literature, then it should be considered a different movement and requires a new set of events to describe it. Our method is adaptable to this situation: there is just a need to provide new training data set and create a new movement type, for example "Sit-Stand with pause". Compared to taylor-made approaches, in which specific functions are developed for each movement type, such as [45], our method provides an easier and more objective way to define new movement types.

In the case of multiple attempts, start over the segmentation should work well, since the segmentation is based on transitions to certain states. However, depending on how or what kind of movement is actually executed, the identification part of the algorithm may fail.

There is also the issue of training data set. The doubt whether the models must be parametrized with data set collected from impaired patients, or whether the models parametrized with healthy individuals data sets is enough. It depends, as in any model and pattern recognition problem there is a trade off between how generic the model is and how precise will be the pattern recognition. For example, according to the literature patients recovering from knee surgery [53], frail elderly patients [24] and obese subjects [23] execute the sit-to-stand slower and with different peak values than healthy subjects, but the overall pattern is similar. In this case our approach will work well if trained only with healthy data, but should improve the performance if patient data is included, as will be shown in Chapter 8. In contrast, severe hemiplegic patients have a different pattern of movement for the sit-to-stand. In this case it comes to the previous discussion of how we define a movement type. It would be then necessary to train different types of movements.

Finally, there is also the concern of how much training data would it be necessary to adapt a certain model to a specific impairment. Since the model is a random variable model, this depends on the ratio of impaired / not impaired examples in the training data set. But as in other random variable models, it is straightforward to update the model with new data and impose a larger weight for some training data set.

7 ONLINE SEGMENTATION AND MOTOR PERFORMANCE PARAMETERS EXTRACTION

7.1 EXPERIMENTS

The purpose of this experiment was to compare the performance of the online estimation with the offline estimation presented in Chapter 6. For each case described in this section, we used the same multivariate SLDS models to run both the online and offline estimation algorithm. These models were obtained following the parametrization procedure shown in Figure 4.1 and therefore resulted in the same SLDS models, including the parameters, used for the experiments in Chapter 6 .

The online estimation algorithm can be used for the segmentation and the motor performance parameter extraction. These two tasks rely on the correct detection of events, either using the multivariate SLDS model for segmentation or using the univariate SLDS model for motor performance parameter extraction. The event detection is done by estimating the value of the hidden switching state s_t at each time step t, which can be accomplished online through filtering.

Movement type recognition, however, cannot be accomplished online simultaneously with segmentation because it requires the time series for each whole movement.. Therefore each movement can only be processed after it is segmented and in this case the procedure is the same used Chapter 6.

The comparison between the online and offline estimation was carried out in two separate scenarios: one for the segmentation task and another for the motor performance parameters extraction.

First, to evaluate the motor performance parameter extraction task, the peak trunk tilt during the Sit-to-Stand movement was estimated using both the SLDS Viterbi and the SLDS Online. Only the intra-subject case (where two data sets from each subject were used for model parametrization a third was used for validation) was investigated. Manually labeled data sets were used as ground truth. The results were quantified using the same metrics applied to the experiment for motor performance parameter extraction in Chapter 6: estimated value, percentage error and delay in the estimation.

Second, to evaluate the segmentation task, the multiple movement data set, 5STS and MWB, were used to compare the performance SLDS Viterbi and the SLDS online. As in the previous case, only the intra-subject (subject specific model) was investigated and manually labeled data set were used as ground truth. To quantify the results, he same metrics used in Chapter 6 were used: sensitivity, false positive and false negative rates.

7.2 SETUP AND PROTOCOL

The same data set from the study presented in Chapter 6 was used to conduct the online experiments.

Seven three three-axis accelerometers from Delsys Trigno Wireless System [3] were placed in the right and left shank, neck and right and left upper arm, all aligned with the frontal for human motion [1]. A 4-DOF biomechanical of the human body was used to calculate absolute angle for each body joint.

Two different sets of movements were performed by six healthy subjects (ages 27-45). One set of movement was a 5 times execution of the Sit-Stand movement (5STS). The other set was a sequence of Mixed Whole Body Movements (MWB), that included one execution of: sit-to-stand, both arms lateral 90^o raise, squat, hip flexion while standing (bow) and stand-to-sit. Each movement set was executed twice by each subject resulting in six different data sets.

The database for this experiment was obtained in Montpellier, France and according to the context, there was no requirement for approval in the Research Ethics Committee.

7.3 RESULTS

Table 7.1 shows the results for the online and offline peak trunk tilt. In most cases there were no delay in the estimation and consequently no estimation error. Errors occurred in only two cases in the online estimation, with subjects 3 and 5.

Table 7.2 shows the results for the online segmentation experiment. The performance of the online estimation was worst than the offline estimation in every metrics used for comparison for both the 5STS and the MWB. Furthermore, comparing only the online estimation between the two data set, the online estimation in the 5xSTS data set was better compared to the MWB in every metric.

Table 7.1: Comparison of offline and online estimation of the trunk tilt angle during the Sit-to-Stand movement. Results shown for each subject in the intra-subject validation. The mean and standard deviation (std) for the trunk tilt is presented, as well as the estimation mean error and standard deviation (std) in percentage. The cases where there was a delay in the detection are also indicated.

	Peak Trunk Tilt	Estimation		
	mean(std)[rad]		Delay in event detection	mean est. error(std)[%]
Subject 1	0.774($\pm$0.024)	Offline	No	0($\pm$0)
		Online	No	0($\pm$0)
Subject 2	0.877($\pm$0.016)	Offline	No	0($\pm$0)
		Online	No	0($\pm$0)
Subject 3	0.778($\pm$0.051)	Offline	No	0($\pm$0)
		Online	Yes	0.5($\pm$0.14)
Subject 4	0.616($\pm$0.104)	Offline	No	0($\pm$0)
		Online	No	0($\pm$0)
Subject 5	0.839($\pm$0.037)	Offline	No	0($\pm$0)
		Online	Yes	0.01($\pm$0.14)
Subject 6	1.034($\pm$0.046)	Offline	No	0($\pm$0)
		Online	No	0($\pm$0)

7.4 DISCUSSION

The capability of online data processing is a required feature in many applications, for example: to provide immediate feedback to patients and therapists. It is also a requirement if used as a part of a control system in an intelligent prosthesis or an alternative communication tool.

In the literature we have found that online segmentation is performed in [34, 33]. To the best of our knowledge there is no proposed general approach for online performance parameter extraction (besides simple threshold based methods). Thus our proposed framework for SDLS modeling and online performance parameter extraction is a novelty.

A general comment can be made to the results in both scenarios: performance parameter extraction in Table 7.1 and segmentation in Table 7.2. As expected, for the same data set and using the same SDLS model, the offline estimation was better than the online estimation in every metric. The reason is that in the offline estimation the same data sample is actually processed twice. As explained in Section 2.4.5, the offline estimation procedure (Viterbi) first estimates each x_t and s_t going forward in every measure in the time-series y_t, from y_1 to y_T.

Table 7.2: Comparison of online and offline segmentation for the 5 times Sit-to-Stand (5STS) and Mixed Whole Body Movements (MWB) data sets in intrasubject validation. Results are presented as a percentage (%) of correct transition detection (C), false negatives (FN) and false positives (FP), within an error bound ($t_{error} < 0.3s$).

			t_{error}<$0.3s$	
data set	Estimation	C	FN	FP
5STS	Offline	100	0	0
	Online	88	12	12
MWB	Offline	96	2	13
	Online	67	33	25

Next, it maximizes the estimation of each x_t and s_t running back in the time-series from y_T to y_1. This means the estimates for x_t and s_t are calculated with measurements from the past and future in reference to t. The online estimation, by contrast, executes only the forward pass in the estimation procedure, as each sample from the time-series y_t becomes available. As a consequence, the estimation of each x_t and s_t are calculated only with measures from the past and the present in reference to t.

For the performance parameter extraction task, the results for the online estimation are similar to the results for the offline estimation. Except for two cases, both the online and offline estimation were able to correctly detect the transition corresponding to the peak trunk tilt and estimate the correct value for this parameter. In the two cases where there was a delay in the online estimation, the error for the estimated parameter was below 1% ($(0.5(\pm0.14)$ and $0.01(\pm0.14)$ respectively). The low error value indicates that there was a short delay in the event detection, which confirms the suitability of the online estimation with SLDS model for performance motor parameters in human movement assessment.

In the online segmentation task, our results are comparable to the results reported in [45] and [33]. The general comments comparing the structure of each procedure in Chapter 6 are also valid for the comparison with the online estimation. The procedure in [45] combines statistical classifiers and a motion signature function to model each movement type for segmentation. This procedure associate different standard procedures and heuristics. The ZVC procedure presented in [33] is sensitive and leads to over segmentation, so some heuristics is used to handle this issue.

Regarding the results, an online segmentation success rate in sequences of repetitive movement of 88% is reported in [45], which is the same rate for the 5xSTS shown in Table 7.2. However, [45] does not specify the t_{error} tolerance used.

As for the comparison of our results with [33], for a sequence of Sit-to-Stand movements, our online estimation was superior to the results reported in [33], (framework presented here: 88% correct detection, 12% false positives, 12% false negatives, approach in [33]: 82% correct detection, 2% false positives, 18% false negatives).

For a data set containing random mixed motions sequence, [33] reported the rates of 90% correct detection, 5% false positives and 10% false negatives. This result is superior to our results presented in Table 7.2, where 67% correct detection, 33% false negatives and 25% false positives. Two factors can explain this difference. First, the data set used to parametrize the segmentation procedure in [33] contained, on average, 20 executions of each movement type per subject. The data set we used in our parametrization, by contrast, contained only two execution of each movement type, which could lead to SLDS models that do not generalize to variation in executions. Second, the data set in [33] was collected using a multi camera marker based motion capture system, which has better precision compared to the sensors we used.

The difference in the online segmentation results between the 5STS and the MWB data set were expected, since the MWB data set contains a greater variety of movement types. A greater variety in the movement types increases the number of parameters in the SLDS model which can lead to errors in the estimation and therefore in the segmentation. Besides, in the MWB data sets, there are two similar movement types, the Sit-to-Stand and squat, that can be confused during estimation.

8 ELDERLY SUBJECTS PERFORMANCE

8.1 EXPERIMENTS

To showcase the potential generalization of the method to populations with limited mobility, the performance for the SLDS model for motor parameter extraction was cross-validated on elderly subjects, some with limited mobility.

A validation experiment was conducted in two parts. First the SLDS model was parameterized with the data collected from three subjects that could execute the STS movement smoothly, as shown in Fig. 8.1a and 8.1b. Next, this model was used to extract two motor performance parameters: peak trunk tilt and rising phase period for the data collected from two subjects with limited mobility.

The parametrization and motor parameters extraction procedures were conducted in the same way as described in Chapter 4 and executed in Chapter 6.

The database for this experiment was obtained in Brasilia, Brasil and according to the context, it was collected within the project approved by the Research Ethics Committee, from UnB - Faculdade de Ciências da Saúde protocol number 47783815.3.0000.0030, title: Reabilitação do Membro Superior Parético pós AVE Utilizando FES e Gamification, granted to Departamento de Engenharia Elétrica da Universidade de Brasília .

8.2 SETUP AND PROTOCOL

Five elderly subjects (three healthy and two with limited mobility, ages 64-88 years) who undergo physical training in a rehabilitation center executed one repetition of the Sit-to-Stand (STS) movement. The database was recorded using a set of 3 three-axis IMU from YostLabs [54]. The sensors were placed in the neck, thigh and shank, also aligned with the frontal plane. Each sensor provides angular position reading, which were combined with a 2-DOF biomechanical model of the human body to extract knee and hip flexion and extension at a rate of 30Hz.

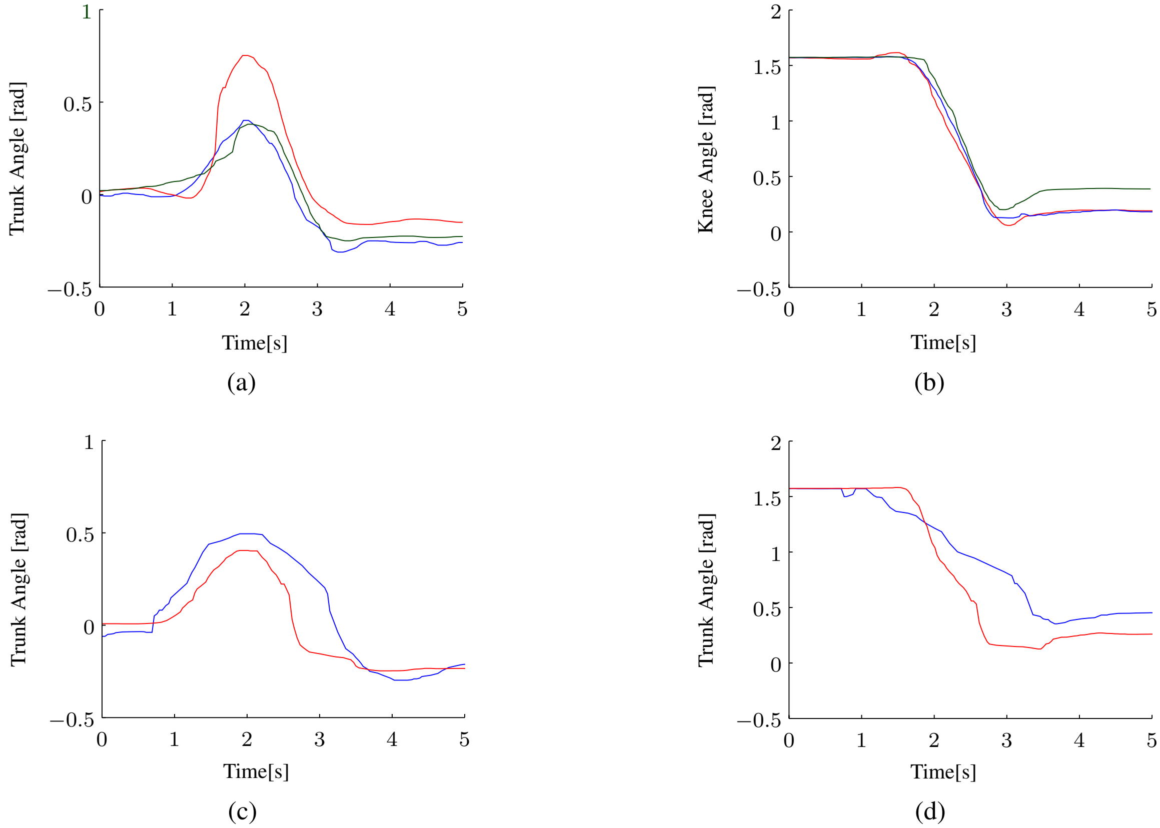


Figure 8.1: Data for case study of elderly experiment. Each colored curve represents a distinct execution. Examples from healthy elderly subjects used for parameterization respectively for (a) trunk and (b) knee angle. Data from elderly subjects with limited mobility used for validation is shown respectively for (c) trunk and (d) knee angle.

8.3 RESULTS

The results for the validation experiments for motor parameter extraction for impaired subjects are shown in Fig. 8.1 and Table 8.1. Movement patterns in the dataset used for parametrization are smoother compared to the movement patterns from the impaired subjects, as displayed in Fig. 8.1. No false positives or negatives occurred in the sequence of events detection and therefore estimation errors are results of delays in the event detection.

Table 8.1: Motor Performance Parameters Extraction results for the proposed algorithm to the Elderly Experiment (subjects with limited mobility, LM) of STS movement in validation.

Variable	Subject	true	estimated	error
Peak Trunk Tilt [rad]	LM1	0.405	0.402	1%
	LM2	0.495	0.443	10.5%
Rising Phase [s]	LM1	2.94	2.33	21%
	LM2	3.34	3.48	4%
percentage error deviation				**9.12%**

8.4 DISCUSSION

This experiment, using data collected from subjects with limited mobility, is a preliminary validation to illustrate the potential generalize movement representation using the method, as well as evaluating its application in a clinical scenario..

Subjects with limited mobility execute the STS movement with reduced smoothness, as illustrated in Fig. 8.1c and 8.1d. This type of pattern deviates from the expected pattern for this movement type which can raise doubt to specialists about the true moment of events. Even with a methodical approach, as presented in Section 2.3, it is not trivial for a human to pinpoint events and therefore establishing a ground truth is prone to subjectivity.

The proposed framework presented in this thesis can handle the reduced smoothness to a certain degree as illustrated by the results in Table 8.1. As mentioned in Section 6.4.3, our framework can handle the reduced smoothness as long as the slope of the time-series in each interval has the same signal (either positive, negative or neutral). Note that we obtained acceptable estimation results on a scenario that would be complex also for a person to classify.

In the case of the segmentation task, the method may be successful to detect the events but not the movement type identification. The movement type identified will be the one corresponding to the SLDS model that yields the lowest cost ($\mathcal{C}$), but it will not truly correspond to a modeled movement type. This issue can be overcome determining a threshold for the cost function to consider the movement as "unrecognized", which is a common solution in pattern classification. Implementation of a software system for clinical application should include this functionality is foreseen as future work.

We have shown also that a SLDS model parametrized with limited data from able-bodied subjects successfully detects the sequence of events in datasets from impaired movements. Recalling the results and discussion from Chapter 6.3.2 in the intra and inter validation, including the dataset from impaired movements should improve the methods performance.

Further investigation regarding the number of dataset for clinical application is a topic for future work.

9 CONCLUSIONS

9.1 FINAL REMARKS

In this thesis, we presented a novel framework for automatic human movement assessment. To address the challenge inherent to automatize the assessment process, this thesis focused on a strategy based on the switching linear dynamic system (SDLS) which has been a cornerstone to the results presented herein. The proposed technique has been assessed with experiments and successfully accomplished the tasks involved in the development of an automated human movement assessment system for a sequence of discrete movements—as shown in Chapter 6. The results herein have been achieved using an analytical procedure based on standard definitions from movement analysis which allows the non-expert users to model, segment and extract motor performance parameters for quantitative assessment.

There is still though the possibility for improvement. For example, in the current development of the framework, a constant velocity model is used to represent the movement during each component. An investigation that belongs to future work is the exploration of other models that compose the SLDS to enhance the algorithm's performance. Furthermore, the results show that model parametrization improves when more training data sets are available. A suitable amount of data necessary to achieve an acceptable model still needs to be studied.

In the online version, presented in Chapter 7, some improvements are also foreseen. A more complex procedure to refine the SLDS model could be to incorporate unlabeled data to update the SLDS models parameters. Such techniques exist in the context of HMM and DBN, they are usually referred to as unsupervised learning. Among unsupervised learning techniques, the most widely used is the Expectation Maximization procedure. One aspect must be kept in mind, our proposed framework was designed to obtain models that follow the definitions from human movement analysis: events, components, phases. The employed of labeled data sets for parametrization procedure presented in Chapter 4 follows the aforementioned context. That is the reason our framework uses labeled data set for parametrization. At some point in our investigation, we did experiment with unsupervised learning techniques for parametrization. These early findings showed that, in most cases, the resulting SLDS models did not match the desired models according to the definitions from human movement analysis. A topic for future investigation could be, however, to have an SLDS model parametrized with our procedure and only refined with unlabeled data sets.

As for the direct application of our method, this framework can be applied in the development of systems for enhanced motor functional testing or monitoring rehabilitation treatment. The framework can also be applied to sport activities since the same principles of movement assessment are used. Experiments in this context are planned. Such systems would provide clinicians (and possibly sports trainers) with a tool to collect an increased number of performance parameters with less effort and improve their analysis. The results using a database from elderly subjects, presented in Chapter 8, indicates that the technique is suitable for clinical applications.

9.2 FUTURE WORKS

Regarding future applications of our proposed online technique, there are two cases which require the employment of online segmentation and/or performance parameter estimation.

First, and most obvious, is to develop a system to provide users with real-time biofeedback and correction hints during movement execution. This feature can be used, for example, during rehabilitation sessions, allowing for automatically supervised home-based rehabilitation or providing the therapist with accurate measures that to aid in the progression of training sessions. Another use can be in a sports training environment, where constant and accurate feedback is crucial for improving technique.

Second is the use of online estimation as a part of intelligent prostheses. Intelligent prostheses are devices that restore motor capability with unnoticeable interaction: the ultimate goal of intelligent prosthesis is to naturally complement the user's limited movements to achieve a task. To achieve this unnoticeable interaction, the posture of both the user and the device must be tracked online. Furthermore, it is interesting to automatically detect events in order to activate or change the behavior of the automatic control system. So far, the automatic control of intelligent prostheses rely mostly in heuristics procedures to detect events and segment movements. Little attention has been given to online event detection and segmentation tasks. We expect that our technique can be adopted in such devices and benefit automatic control systems in intelligent prosthesis.

Finally, providing machines with the ability to automatically recognize and quantify human movement, can open the door to new kinds of human-machine interface. Gesture recognition has been gaining attention lately, specifically in alternative communication systems. Body movements recognition and assessment amplify these possibilities.

In summary, we believe the proposed framework is a step towards the development of automatic human movement assessment tools. Coupled with the widespread of portable low-cost movement sensors, these tools will deeply impact the future of augmented biofeedback, telerehabilitation, intelligent prosthesis and human-machine interaction.

PUBLICATIONS

Besides this manuscript, the results of the work developed during my PhD were published in one journal, three international conferences, one national conference.

R. D. S. Baptista, A. P. L. Bó and M. Hayashibe, “Automatic Human Movement Assessment with Switching Linear Dynamic System: Motion Segmentation and Motor Performance” in IEEE Transactions on Neural Systems & Rehabilitation Engineering. (Qualis CAPES A1) (Accepted for publication, DOI: 10.1109/TNSRE.2016.2591783, early access available at: http://ieeexplore.ieee.org/document/7513405/)

R. D. S. Baptista, A. P. L. Bó and M. Hayashibe, “Methodology for automatic movement cycle extraction using Switching Linear Dynamic System,” in 2015 7th International IEEE/EMBS Conference on Neural Engineering (NER), 2015, pp. 743–746.

Bó, A.P.L. and Baptista, R. S. "Online Cyclic Motion Modeling and Feedback for Physical Training and Rehabilitation" in: XXIV Congresso Brasileiro de Engenharia Biomédica - CBEB, 2014, Uberlândia. Anais do XXIV CBEB, 2014.

J. Zhao, K. Berns, R. D. S. Baptista, and A. P. L. Bo, “Design of Variable-Damping Control for Prosthetic Knee based on a Simulated Biped,” in IEEE International Conference on Rehabilitation Robotics, 2013.

J. Zhao, K. Berns, R. D. S. Baptista, and A. P. L. Bo, “A Comparison of a Passive and Variable-Damping Controlled Leg Prosthesis in a Simulated Environment,” in International Conference on Climbing and Walking Robots and the Support Technologies - CLAWAR, 2013.

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RESUMO ESTENDIDO EM PORTUGUÊS

Contextualização

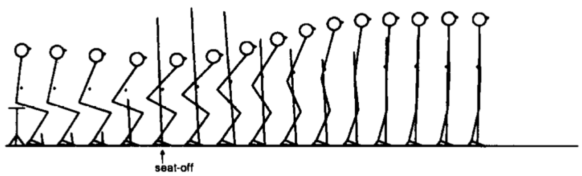
A ciência do movimento humano está à beira de uma revolução. Sensores portáteis e de baixo custo estão rapidamente abrindo caminho em atividades cotidianas, fornecendo medições de movimento humano previamente reservadas a equipamentos de laboratório e procedimentos complexos. A quantidade e a disponibilidade de dados quantitativos sobre o movimento humano terão impacto direto em muitas áreas, tais como: esportes, reabilitação e interação homem-máquina.

Nos últimos anos, foi dada muita atenção à descrição objetiva baseada em evidências de movimento, aprendizagem de controle motor com feedback aumentado e telerehabilitação. Da mesma forma, tem sido dada muita atenção à tecnologia de sensores portátil e de baixo custo para medições de movimento humano. Em contraste, pouca atenção tem sido dada à avaliação automática de movimento. A avaliação através de medidas indiretas são as informações quantitativas que um profissional utiliza para avaliar a qualidade do movimento. A razão é que as tarefas de automatização aparentemente fáceis para os seres humanos - como reconhecer os movimentos, determinar o início eo fim de um movimento e observar as principais características do movimento para julgar a sua qualidade - exige de um lado profunda compreensão da natureza humana das tarefas a serem automatizadas e de outro lado avançados modelos matemáticos e técnicas complexas de aprendizagem da máquina. Nesta tese automatizamos o processo de segmentação, reconhecimento do tipo de movimento e avaliação.

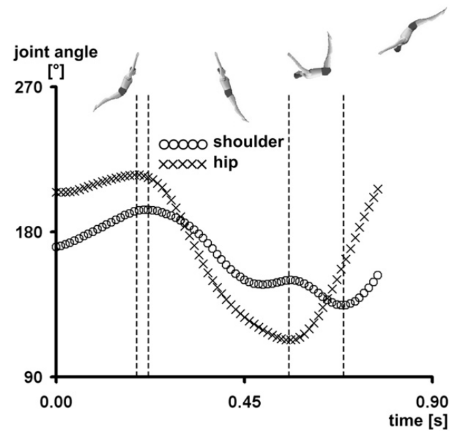
Fundamentação teórica

A motivação de qualquer avaliação é permitir uma decisão positiva sobre um movimento físico. Um instrutor atlético pode verificar se uma variação de determinada técnica irá minimizar a energia mecânica necessária para um determinado movimento. Um cirurgião ortopédico pode querer observar melhorias na força do joelho de um paciente um mês após a cirurgia. Um pesquisador pode querer interpretar as mudanças motoras devido à perturbação controlada para verificar ou negar diferentes teorias de controle neural [4].

As descrições são formas de representar medições para facilitar a avaliação. Elas podem



(a) Diagrama do movimento levantar [15].



(b) Gráfico da série temporal de ângulos de juntas em um movimento de ginástica artística [16].

Figura 9.1: Descrições de movimento.

assumir a forma gráfica, tais como: gráficos de séries temporais, diagramas de ciclo de movimento ou diagramas de movimenos, como mostrado na Figura 9.1. Alternativamente, eles podem ser uma fórmula matemática que resulta em uma medida de resultado, tais como: velocidade da marcha ou altura máxima de um salto. Ao longo desta tese, as medidas indiretas serão referidas como parâmetros de desempenho motor.

Uma maneira de descrever sistematicamente um movimento é dividi-lo em elementos de acordo com a mudança na tendência de séries temporais cinemáticas e / ou cinéticas, como flexão e extensão, de cada articulação do corpo e seus efeitos nas mudanças de postura.

Tomamos as seguintes definições usadas por [20] para descrever sistematicamente os movimentos discretos:

• Eventos (e) é uma única ocorrência identificável de uma mudança na tendência do padrão de movimento registrado para cada variável cinemática ou cinética.

• Componentes (c) são definidos como as partes constituintes do movimento que são delimitadas por eventos dentro da mesma variável.

• Fases (p) são construídas a partir de componentes e também são delimitadas por eventos, mas os limites podem ser estabelecidos usando eventos de diferentes variáveis.

• Movimento (m) é uma seqüência de uma ocorrência de todas as fases entre duas posturas distintas.

Em relação ao modelos matemáticos para representar movimento humano, usando modelos ocultos de Markov (HMMs), é possível decodificar uma seqüência de estados discretos

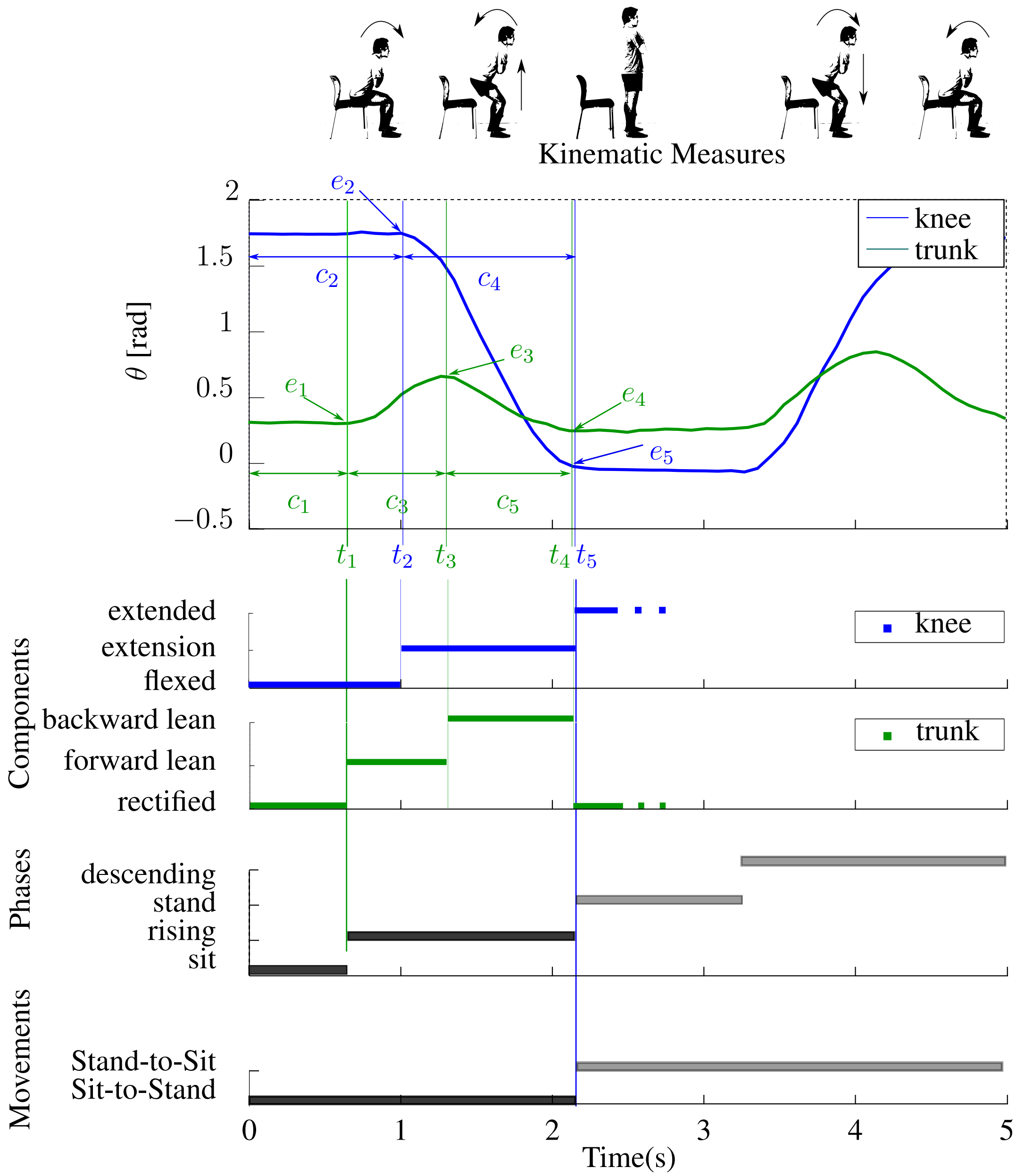


Figura 9.2: Descrição de movimento de acordo com as definições de eventos (e), componentes (c), fases e movimento.

- geralmente, discretos e finitos - mas não conseguimos rastrear os valores contínuos entre os estados. Pense nisso como uma seqüência de fotografias, onde podemos estimar a seqüência de poses que gerou essa seqüência de fotografias, mas somos incapazes de descrever os movimentos entre poses usando um HMM simples. Em contraste, o filtro de Kalman (KF) acompanha com sucesso os movimentos lineares contínuos ao longo do tempo — por exemplo, o KF pode ser usado para rastrear um movimento particular do corpo. Podemos pensar em um observador seguindo o movimento em um filme gravado. No entanto, apenas um modelo é usado para representar o movimento e este modelo é linear — conseqüentemente o filtro de Kalman só pode rastrear um movimento simples e limitado de cada vez. Além disso, uma vez que se baseia num modelo único, a técnica não é adequada para segmentar uma sequência de movimentos.

Um sistema dinâmico linear chavedo (SLDS), em essência, combina um modelo oculto de Markov com a filtro de Kalman. Assim, podemos pensar nos elementos básicos do SLDS como curta-metragens de movimentos simples entre duas poses. Combinando a seqüência desses elementos básicos, podemos representar um movimento consideravelmente mais complexo e completo. Como sabemos qual conjunto de elementos básicos são usados para representar cada movimento, também podemos usá-lo para segmentar e reconhecer uma seqüência de movimentos em um dado filme e dividir cada movimento para analisar poses ou transições críticas.

Método proposto

No atual estado da arte existe uma falta de métodos que representam com êxito o movimento humano medido por sensores arbitrários e permite simultaneamente a segmentação e a extração de parâmetros motores. A primeira contribuição desta tese envolve a integração de ferramentas matemáticas e seu uso combinado para executar tais tarefas.

Primeiramente, mostramos que SLDS se ajusta diretamente às definições de análise de movimento humano tradicional e resolve as duas tarefas (segmentação e extração de parâmetros motores) de forma sistemática e unificada. Cabe ressaltar que uma solução para o problema de usar uma única técnica de processamento de sinal para ambas as tarefas ainda não foi proposta.

Para atingir esse objetivo a partir de dados multivariáveis, é necessário não apenas analisar o comportamento de todas as variáveis cinemáticas simultaneamente, mas também analisar cada variável separadamente. Analisar todas as variáveis cinemáticas ao mesmo tempo é útil para representar o padrão de movimento global que é necessário para alcançar a tarefa de segmentação. Isso representa as ações coordenadas de diferentes partes do corpo que resulta

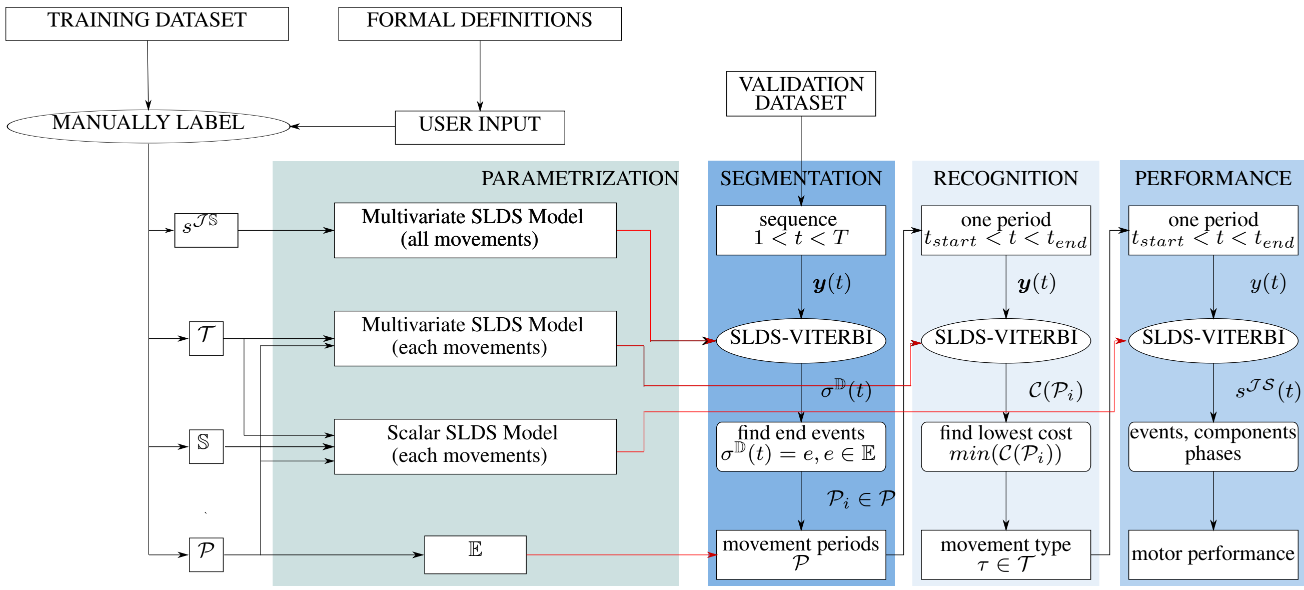


Figura 9.3: Diagrama de blocos do método proposto.

no que chamamos um tipo de movimento. Um exemplo é o padrão de flexão e extensão do tronco e das pernas necessárias para executar o movimento levantar-se da posição sentada. No entanto, extrair parâmetros de desempenho do motor requer uma análise específica de cada variável cinemática. Por exemplo, para extrair a inclinação do tronco de pico durante o movimento de levantar-se, devemos analisar apenas o ângulo de tronco variável cinemática. Uma visão geral é dada na Figura 4.1.

O nosso método é composto de um modelo escalar SLDS - o que significa que x_t e y_t no modelo SLDS são escalares - que serão usados para detectar mudanças na tendência para apontar eventos e determinar os componentes para cada variável cinemática. Em seguida, utilizamos um SLDS multidimensional - formado com a combinação dos modelos escalares SLDS - para rastrear todas as variáveis simultaneamente que serão usadas para determinar o início e fim de cada movimento e também reconhecer que movimento é executado.

Finalmente, nosso método inclui um procedimento que parametrização do modelo SLDS a partir de dados rotulados. Desta forma, o método pode ser usado por pessoas que não possuem conhecimento em processamento de sinais ou modelagem matemática.

Contribuições

As principais contribuições desta tese podem ser resumidas como:

1. **Abordagem matemática unificada para segmentação automática, reconhecimento de tipo de movimento e extração de parâmetros de desempenho motor:** diferente

dos trabalhos anteriores na literatura, utilizamos os mesmos procedimentos de modelagem e estimativa matemática para resolver as tarefas necessárias à automatização da avaliação humana. Isso simplifica a implementação de software, parametrização do modelo e aplicação do método a qualquer tipo de movimento descrito por parâmetros cinemáticos.

2. **Procedimentos de parametrização que não requerem antecedentes no processamento do sinal:** o método proposto usa conjuntos de dados rotulados manualmente para parametrizar automaticamente os modelos matemáticos. Portanto, profissionais sem experiência em processamento de sinais podem usar diretamente o método proposto sem a necessidade de entender a matemática subjacente.

3. **Implementação e validação em diversos experimentos:** implementamos nosso método e testamos em diferentes condições com população variada para mostrar desempenho e aplicabilidade.