RULE BASED BEHAVIOR CLASSIFICATION VIA ACCELEROMETRY IN TRANSTIBIAL AMPUTEES

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ABSTRACT

Rule Based Behavior Classification via Accelerometry in Transtibial Amputees

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A high-performing and comfortable prosthesis follows from an understanding of how amputee activity modulates residual limb volume and socket fit. There are currently very few systems available which capture general long-term amputee behavior and so a computer algorithm for categorizing activity data is developed and validated. An accelerometer is fixed to the prosthesis pylon and reliably captures long-term natural transtibial activity. Data are downloaded and processed in a rule-based decision tree algorithm wherein regions are categorized into human behavior models, called schema, representative of a wide range of activities. After validation and optimization, algorithm overall effectiveness was graded at 92.36% with 100.00% active/passive activity differentiation. Through examining the activity of transtibial amputees and their prosthesis relationship made possible by this work, improvements can be made in prosthesis treatments, design, materials, and adaptive technology that will result in a better fitting, more secure, and empowering prosthesis.

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GLOSSARY

AM:	Activity Monitor(ing)
ARMA:	Auto-regressive Moving Average
FFT:	Fast Fourier Transform
FIR:	Finite Impulse Response [filter]
GTD:	Ground Truth Data
MFCL:	Medicare Functional Classification Level
MEMS:	Micro Electromechanical Systems
MF:	Median Filter
ML:	Machine Learning [scheme]
RB:	Rule Based [scheme]
SMV:	Signal Magnitude Value

ACKNOWLEDGMENTS

I would like to extend my gratitude towards the supportting members in this endeavour of mine:

to Christian, monumental in every way;

to John, who kept things greased;

to Paul, who is building the future;

to all the other experamentalists who fielded questions and inspired me;

and to Dr. Sanders, who has been a constant encouragement.

DEDICATION

My effort here is dedicated to my lifelong friend,

confidant, and inspiration, Jarica.

Without my sister I would not be where I am today.

Here’s to running against the wind.

CHAPTER 1: INTRODUCTION

Categorization of human behavior has been a taxing effort to the field of biomechanics for the past century. Specifically, the challenge lies in non-invasive (and more specifically, unobtrusive) systems which accurately identify the variety of behaviors present in human activity. The work here describes how daily lower limb amputee behavior is captured using limited, and robust instrumentation and classified with a novel algorithm. The implications of these developments aim to service research and treatments that progress the field of prosthetics and beyond.

According to a recent study, there are an estimated one and a half million individuals in the United States who have suffered the loss of a lower limb through the woes of cancer, trauma, or dysvascular disease with this number predicted to double in the next fifty years [1]. As medical science and technology advances, treatment options including amputation will increase [2]. Such treatments offer solutions to traumatic injuries from motor-vehicle events, natural disasters, military conflicts and war, and to non-traumatic sources as access to diabetes treatment increases [2].

For individuals who have an amputated lower limb, achieving typical social functionality is greatly tied to the quality of life and mobility of the individual. Results conclude that for those who choose to utilize a lower limb prosthesis, quality of life is higher on average than those without prosthesis aids [3].

The build, suspension, fit, and comfort of the prosthesis mustn't hold back an amputee from social normality. Personal lifestyle is a main factor on prosthesis design [4] and amputees can choose the socket type, socket liner, foot, pylon, and other components with a prosthetist to optimize usability and comfort for their activity range [5] [6]. A well-fitting prosthesis is crucial in order to enable not only functional mobility but enjoyable mobility.

The interplay between socket fit, residual limb (residuum) volume, and activity level is complex, but in understanding this we move closer to ensuring optimal and enduring user comfort and mobility for the amputee community. An amputee's residuum is a dynamic biological entity, responding to factors such as hydration, diet, postural orientation, activity history, and don/doff history, to name a few [7]. A prosthetist's fitting of a residuum captures a moment in time, a volume conformation which is a function of the particular response parameters up to that moment, and may not be optimal for other life moments such as during high activity after the residual limb volume has changed [8]. Volume change in the residuum can result in general tissue irritation and subsequent breakdown after extended use, especially in an ill-fit socket [9]. This discomfort is a main factor in amputees choosing the disuse of their prosthesis which typically, as was stated, negatively affects their quality of life [10]. Clinicians and researchers then are presented with the challenge of improving comfort and fit of lower limb prosthesis. Knowing that activity affects comfort, capturing accurate user lifestyle activity will contribute to a body of biometric data acting to improve amputee quality of life.

The introduction of reliable and robust activity monitoring for lower limb amputees can offer insight into how activity affects fit, comfort, and quality of life. Beyond clinical applications, research into the effectiveness of treatments and socket components can be assessed, evidencing further support from insurance and development companies [5].

Daily "free living" prosthesis user activity monitoring ("AM") has been complicated by the complexity of human life. Where monitors have been developed for individuals of normal body and health, i.e. FitBit, Jawbone, and the Nike Fuelband, a device specific to the reliable, robust, and nonspecific activity capture and categorization of lower limb amputees has been rare [11] [12] [13]. The particularities of an individual with limb loss's usage of their prosthesis, in spite of its worth to the prosthetics community, has remained shrouded and difficult to quantify [14].

Current metrics relating to lower limb mobility include the timed "up and go" and the six-minute walk [15] [16]. Each of these assesses mobility in general populations but often are extended to a prosthesis user in a laboratory setting [17] [18]. As most individuals do not spend the majority of their days in a laboratory, other systems have been developed in attempts to capture the daily prosthesis-user activity.

Current daily long-term activity monitoring systems specific to lower limb amputees, upon inspection, have several main deficiencies. Power conservation is an issue with all on-board electronic systems. If the AM is required to be removed and recharged each evening this holds the user liable for its ultimate functionality. If the AM is capable of only capturing a day or two of activity under non-rechargeable power then long-term monitoring is problematic. Another issue is the system's specificity to the task. In order to be robust and applicable to free living conditions, the AM must capture activity in various behavior domains efficiently. Many daily AM studies are designed for gait analysis or a specific activity, lacking proficiency in capturing other aspects like posture or a doffed prosthesis. Other studies require strict adherence to behavior restrictions. In general, an AM system needs to be designed that is robust to capturing the variability in human lower limb prosthesis user activity, and reliable; requiring little to no user involvement in its usage.

1.1 Thesis Goals & Contributions

The thesis presented here details the development and implementation of a transtibial prosthesis AM system and categorization algorithm. While testing was limited to transtibial amputees, conceivably the algorithm would be extendable to other lower limb amputees. The use of a single commercially available 3-axis accelerometer simplifies instrumentation, user involvement, accessibility, and repeatability. The accelerometer is instrumented on the prosthesis' distal lateral pylon and is capable of capturing long-term data. Once a collection session is complete, these data are offloaded for processing by the algorithm, producing a behavior time series and other secondary outputs. From the products of the algorithm prosthetists and researchers can identify core activities or behaviors contributing to user discomfort and poor prosthesis performance.

The premise of the work presented here is whether minimal instrumentation on a transtibial prosthesis is capable of providing appropriate activity data for the developed algorithm to process, ultimately resolving behavior information useful to clinicians and researchers. The offline (post-collection) algorithm has been built to categorize behavior in detail, differentiating between such archetypal human behavior categories as walking, prosthesis doffed, lying down, inverted, standing, etc. Beyond behavior information, the algorithm is capable of presenting interesting lifestyle relations from collection sessions to be utilized by prosthetists and researchers, i.e. total or momentary duration in a particular behavior, number of transitions between behaviors, walking speed preference, and average gait parameters. These heuristics are currently lacking in the field of lower limb amputee treatment. From these results, prosthesis fit, build, and suspension can be optimized to the individual's lifestyle, the individual's health and mobility can be assessed, and recommendations on how to feel more confident and comfortable in their prosthesis can be offered.

This efficient and minimal algorithm will ultimately be developed into a real-time on-board processing system actively controlling the moment-by-moment prosthesis socket volume.

CHAPTER 2: BACKGROUND

As was implied in the introduction, activity monitoring is not only clinically significant, but a task which can and has been investigated by many other fields. Because of the attractiveness and wide use, activity monitoring has seen multiple methods developed, stemming the gambit from self-reporting procedures to computationally expensive predictive modelling. Here, related methods and their relevance to the prosthesis community are discussed with a specific focus on the role accelerometry plays in AM.

2.1 Activity Monitoring in Prosthesis Users

Activity monitoring generally falls into two categories: passive and active reporting, relating to the role of the subject in data collection. Active monitoring involves active record keeping from the subject (i.e. self-activity reports), often inherently lacking outside validation. Passive recording involves a monitoring device such as, but not limited to, a time-stamped video recording or a device capable of capturing activity (i.e. pedometer). Active methods seek broad components of prosthesis use, such as duration and frequency of wear or common behavior [19]. Even given the broader strokes of self-reporting, it is noted as unreliable within the prosthesis user community when compared alongside a step activity monitor [20].

Recently, passive monitoring is the more widely used method in the prosthesis-wearing community with pedometers, step-counters, and other ambulation-specific devices capturing activity over periods of individual use [21] [22] [23] [24] [25] [26]. Because these devices are limited in what activity they capture, other activity monitoring systems and processing have been developed, encompassing not only ambulation activity like step counts and gait dynamics, but also postural orientation activity [27] [28] [29] [30]. Several sensor systems have been developed which capture these data from sensor systems over short time durations up to a few hours [31] [32] [33]. These current systems which measure body activity beyond step-specific measures still possess clinical and real-world challenges. Primarily, there exists a main restriction to short-term study; on-board memory and battery life contribute chiefly to this. Second, user rules and regulations inhibit natural activity through compliance to strict protocol, intrusive or abundant sensors, and instrumentation requirements. From this, a niche for a robust, cheap, and simple activity monitor capable of capturing various bodily activities is identified. The need for unobtrusive instrumentation guaranteeing near freedom of natural activity that collects data, offloads, and processes it using an activity categorization scheme finding relevant categories and relationships is higher now than ever.

2.2 Activity Categorization Approaches & Methods

Passive approaches to activity monitoring therefore present themselves as the optimal means for reliable and unobtrusive activity capture. These systems employ one or more sensor types to collect data over the prosthesis' use. Data are offloaded from the on-board system memory for increased processing capacity. Multiple processing algorithm approaches have been developed to analyze activity.

Activity can be captured via a wide array of sensors. Force sensors (force sensitive resistors, FSRs) have been utilized in both a plantar and prosthesis socket positioning [34]. Proximity sensors measuring distance between interfaces and examining socket-residuum distance (or simply just the occupancy of a socket), yield information on activity [35]. A plethora of other possibilities exist, though none have proven as ubiquitous as the three-axis accelerometer, the chosen device of this and many other studies [36] [37] [38] [39] [40] [25] [28] [41].

2.2.1 Accelerometers in Activity Monitoring

The multitude of uses for an accelerometer chiefly attribute to its success in this and related fields. Their capabilities extend not only to activity monitoring, but gait analysis [30] [23] [42] and postural orientation [36] [40]. Multiple features can be extracted from acceleration time series. Given a uniform sampling frequency, the principle linear acceleration component arrays can produce gravitational acceleration signals for orientation, bodily accelerations, act as inclinometers, relate to device activity, and generate or contribute to many others. Advancements in microelectromechanical systems (“MEMS”) allow for three orthogonal accelerometers to occupy infrastructure smaller than a match head [43]. Given their low power draw and environmental robustness, accelerometers are an efficient choice for lasting activity monitoring [28].

Accelerometers measure the acceleration of the device along three axes. One or more axes will register gravitational acceleration (typically calibrated at 1g). During staticity, this information can be used to orient the device (as an inclinometer [28]), but during activity the bodily, gravitational, and noise components must be separated. These de-noised components provide information on not only acceleration, but velocity, position, impulse, and orientation that can be harnessed in the categorization of activity. Various analyses can be imposed on these signals, such as population metrics like mean, median, skewness, kurtosis, etc., or series metrics like Signal Magnitude Value (“SMV”). Transforms of these signals provide yet more categorization evidence, with frequency domain methods such as Fast Fourier Transforms ("FFT"s) and Wavelet transforms occurring most often [28] [44] [24].

There are many commercially available accelerometer units capable of consumer exercise monitoring or clinical/research applications. Popular fitness trackers focus on delivering intuitive measurables for public use, such as caloric expenditure, step counting, or overall activity, and do not provide raw data to users nor information on posture or behavior specifics [11] [13] [12]. Often a general summary of activity is presented to the user. This is not useful within a clinical or research setting if user activity specifics are desired. More appropriate to these studies are products such as the ActiGraph wGT3X-BT Activity Monitor or OrthoCare StepWatch which have been featured in numerous activity monitoring experiments [22] [23] [20] [28] [25] [26].

Activity monitoring using accelerometry presents challenges to both the measured and measurer. Proper placement of the sensor is of paramount importance. The location must be such to capture wanted activity, i.e. body segment posture, periodicity, or orientation, but not undesirable jitters or other noise. Typically, accelerometers are placed on bony landmarks (i.e. greater trochanter or malleolus) or locations of little skin drift (wrist), though placement on biological tissue is not an issue in this study. The accelerometer fixation needs to be steadfast and remain as such. Any relative movement between sensor and the target body segment results in spurious data, so care must be taken to secure the device. The subject must also contend with the instrumentation. Wiring, fixations, obtrusiveness, and the inertia of the device must be considered to ensure natural behavior.

The processing of accelerometer data takes two widely used forms; rule-based schemes or machine-learning algorithms. Rule-based schemes ("RB") follow decision architecture structures to resolve a desired output. Machine learning approaches ("ML") interpret data using network models, graphs, or other methods and training data. RB schemes are presented here based on their popularity and ease of implementation and interpretation [45]. A RB scheme is also used in the algorithm described in this thesis. For completeness, ML approaches are presented as well to outline their strengths and weaknesses. Both approaches are widely used to classify objects, but differ on the pathway taken to arrive at the sorted output.

2.2.2 Machine Learning Approaches

Given definable categories which data are to be sorted to, a ML approach is suitable. A ML algorithm requires sample data which is representative of the target data. This sample data is known and classified (manually or through a RB scheme) as ground-truth data ("GTD"). A ML algorithm reads these truths to improve processing of target data. ML algorithms recognize target data as matching a category of the GTD and process in this manner [46].

Validation of ML approaches involves examining classified data of which the algorithm was not trained on, often accomplished by halving sample GTD, training with one half and validating with the other [47]. A level of simplification is imposed through identification of target data features which correspond to the desired categories. These feature vectors are often selected through insightful inspection or obviousness and represent the distinct features characterizing the ultimate output categories of the algorithm. Before training, sample data or feature vectors are transformed in some capacity to limit noise or extraneous features to aid in categorization. Overall computation time and accuracy are hugely benefitted through feature selection and transformations [47] [46] [45]. One common ML approach is hereafter presented.

K-Nearest Neighbor

This approach is typical of ML algorithms as it sorts objects based on optimal but sometimes unintuitive (non-human generated) criteria. Data are curated, collecting regions which responsibly and cleanly encode for a feature describing the target data. These strings are deemed feature vectors and the collection of them define as comprehensively as possible the complete set of ultimate category features of the target data set. These feature vectors are organized into a high-dimensional parameter space representative of the training data for which the target is to be compared against. This space encodes for all possible feature variations in the target data. Feature vectors should separate and disperse within this space, demonstrating that they cover many of the possible features. Target data is selected (in AM usually just a region of data) and allowed to orient in the parameter space for categorization.

The categorization process of the nearest neighbor approach is sensitive to the relatedness between the target data and feature vectors. Based within the parameter space, a measure of the relatedness between target coordinates and feature vector coordinates is calculated. A coordinate within this space is high-dimensional, as the space encompasses most possible feature dimensionalities of the data. A Euclidean distance is calculated between target and each feature point at each dimensionality, i, i.e. $d_i = \sqrt{\sum_{i=1}^{N}(S_i - X)^2}$ where d_i is the target-feature distance of the i-th dimension (or i-th feature), S_i is the i-th classified feature vector coordinate, and X is the input target coordinate. The K features which minimize distance (maximizing relatedness) are selected to build a category estimation for the target. A category estimate can be built from simple prominence or from a distance-weighted method. In the first approach, the most represented feature in every dimension from the K nearest neighbor vector collection are used to construct a category estimate for the target, i.e. the mode of the *K* neighbors. In the other, the features' affects are graded by their distance to the target in each dimension. Once a category has been estimated for the target, it is assigned and subsequent target regions are similarly classified.

This ML approach assumes targets are disjoint, often segmenting a time series on some level to better classify regions. While not always valid, assuming features describe perfectly disjoint regions of data has proven suitable. In one study, a *K*-Nearest Neighbor ML algorithm was utilized to differentiate typical human gait from atypical. After the generated accelerometry series were subjected to independent component analysis to identify applicable features, the study found near 100% categorization accuracy [44]. While still a nice result, the required pre-processing and analysis is not applicable to this study, or any real-time activity monitoring systems.

2.2.3 Rule Based Schemes

Rule based schemes follow decision architecture to arrive at a known and appropriately characterized category. The process of arriving at these output categories follow set rules designed either manually or via some algorithm process. In regards to activity monitoring, categories may represent behaviors or activity levels. Categorization is a process of progressing along the decision architecture, comparing the output of the prior decision to the criteria leading through the next. At the terminus of these pathways is often a catch-all category which captures unclassifiable data. This architecture is often described as and takes the form of a "tree" [40]. RB decision tree schemes are intuitive to interpret and straightforward in their design. ML processes are often puzzling in their decisions whereas RB schemes are almost state-like in their functioning and easily debugged.

Rules built into the architecture decide the progress and eventual category of the input data. While these rules predictably determine the fateful output, considerable thought must be put into their generation. Rule determination is a labor intensive process and must be true in its conclusions else risk inaccurate decision outcomes, such as misclassified data. Decisions pivot on the heuristics set by the rule makers, with the heuristics aiming to differentiate data based on intrinsic disjoint features (similar to feature vectors in ML approaches). It has been found that categorization rules generated manually better generalize to a variety of subjects over computer generated rules [45]. In this way rules are based on an overview of general subject trends rather than an “overtrained” ML scheme which performs well due to its preference towards a particular collection of training data.

The simplicity with which RB schemes classify data and their nonspecific heuristics generated by (presumably) knowledgeable and experienced researchers have proven successful in many studies. Regarding accelerometry categorization, many studies have employed a RB scheme to identify subject posture and activity [45] [40] [37]. To appropriately classify target data, time series are broken into regions, each analyzed via a RB scheme. These regions are further decomposed into continuous sub-categories until a terminal category is reached. Due to the obviousness and prominent features, it is often high level activity for example which is first to be classified in a RB hierarchy architecture with subsequent sub-active categories characterized from there. Each region, as is the case with target data in ML approaches, is treated as disjoint from one-another, though this is not an ultimate condition and is often relaxed in RB schemes.

This thesis implements a RB scheme to classify accelerometry data. The architecture is linear in decision-making but not a perfect tree with disjoint branches (some categories can be arrived upon through multiple pathways). As the algorithm's goal is to remain nonspecific and simplistic, the scheme is generic yet robust to the domains of human behavior, and reliable, with portions eventually extendable to a real-time categorization system. The output behavior time series is sensitive to subject posture, activity, and other factors contributing to residuum volume change and overall comfort, providing a useful and needed assessment tool for clinicians and researchers.

CHAPTER 3: METHODS

A single 3-axis accelerometer (ActiGraph wGT3X-BT Activity Monitor, Pensacola, FL.), is mounted to the lateral aspect of the prosthesis pylon or leg. Data are collected under a prescribed activity series in and around the laboratory from 11 subjects. Data are downloaded from the AM and processed upon returning to lab. A time series indicating estimated behavior is generated alongside useful secondary results. The procedure of data collection and processing is now detailed.

3.1 Instruments & Participants

The AM has a dynamic range of $\pm$8g (where 1g is 9.81m/s^2, the acceleration due to gravity at sea level), 0.00293g resolution, sample rates between 30-100Hz, and a battery life of ~25days (capable of collecting data continuously for this duration). A dynamic range of $\pm$6g has been previously found acceptable for capturing human activity [48] [42]. Its mean weight, 19 grams, is insignificant compared to the weight of the average transtibial prosthesis. The AM is robust to daily environmental and usage conditions (temperature, moisture, shock, etc.).

Participants of this study were recruited to test the validity of a behavior categorization algorithm in a semi-controlled activity protocol. All subjects were recruited from local prosthetic clinics, peer support groups, and hospitals. Inclusion criteria were ages 18 to 75, transtibial amputation that occurred at least 2 years prior to testing, Medicare Functional Classification Level (“MFCL”) 2 (limited community ambulatory) or higher [49], a healthy residuum with intact skin, and the ability to walk for at least one hour (with rests as necessary). Subject pool is presented in Table 3.1 with population statistics presented at bottom. The average age is 50, (min. 29, max. 68) and the average time subject has been an amputee is 14.3 years (min. 4, max. 60). Data for some subjects were not available.

Table 3.1 Subject demographics.

Subject	Limb	MFCL	Sex	Age	Amputation Duration [yrs]	Weight [kg]
1	R	2	F	68	60	*NA*
2	L	2	M	54	7	115.7
3	L	2	M	51	6	106.6
4	L	3	M	52	7	84.0
5	L	4	M	51	24	101.8
6	L	3	M	29	10	48.3
7	R	3	*NA*	*NA*	*NA*	99.8
8	R	3	M	61	7	88.4
9	L	2	F	58	12	103.4
10	L	4	M	39	6	95.2
11	R	3	M	34	4	84.5
μ				50	14.3	92.8
σ				11	15.4	16.8

3.2 Data Collection

In data collection trials, the AM is first activated and two-sided Velcro tape fixes it to the pylon of the prosthesis, oriented such that its x-axis is aligned axially (up the limb) and its y-axis is aligned anteroposterior (making the z-axis aligned medial-lateral), see Figure 3.1. It is further affixed with a Velcro strap around the pylon, and then covered and secured in medical pre-wrap tape. At times, a foam spacer is used to ensure a conforming and solid meeting between the AM and pylon. Limited "jittering" is optimal to capture accurate accelerometry signals and to remain unobtrusive to user behavior. A note about placement; there are many regions which have been studied for accelerometer placement for activity monitoring but two reasons limit location to the pylon:

1) Future laboratory instrumentation will be focused on the pylon that will include an AM.

2) The orientation and kinematics of the lower leg prosthesis yields crucial activity information absent at other sites (i.e. during sits and stands hip orientation shows little to no variance in orientation while lower leg orientation can vary drastically).

During the prescribed activity, subjects adventure around the laboratory building and grounds, sitting or standing at defined points, walking around, riding elevators, or donning/doffing their prosthesis as an attendant dictates and catalogues the ground truth behavior (“GTD”). Sessions are typically 30-50 minutes. Upon completion, the subject’s prosthesis is relieved of the AM, and the raw data are downloaded for processing.

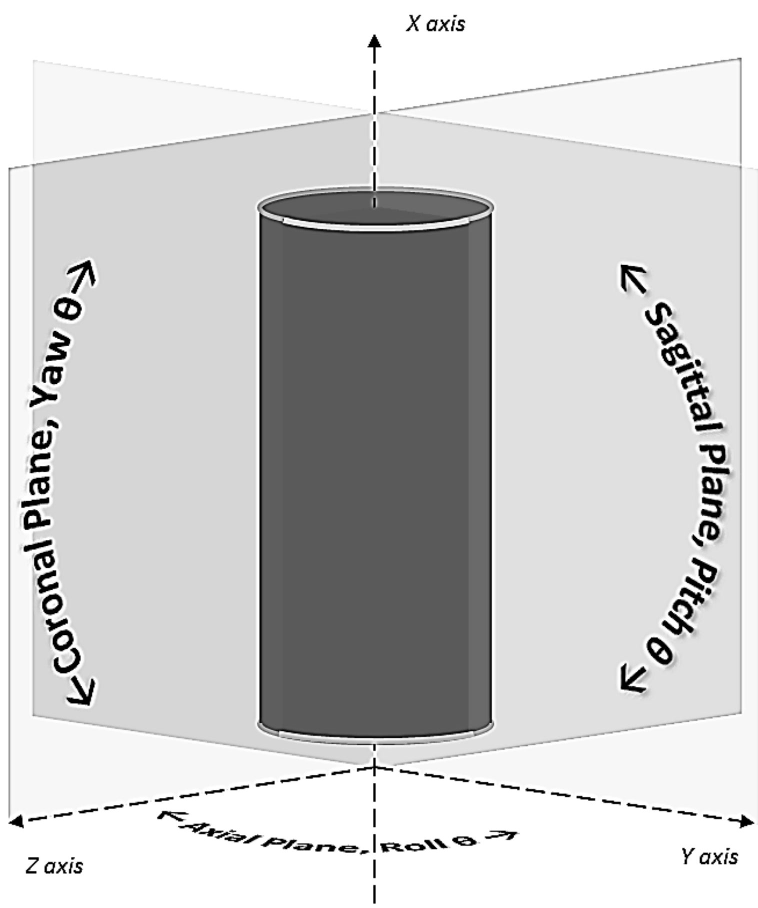

Figure 3.1 Orientation of the ActiGraph Activity Monitor (AM, it is mounted at the distal lateral leg region (pylon). The x-axis aligns longitudinally (normal to axial plane), the y-axis aligns anterior-posterior (normal to coronal plane), and the z-axis aligns medial-lateral (normal to sagittal plane). Motion along these planes is known as roll, pitch, and yaw, respectively.

The ActiGraph produces four arrays of data: the timestamp of each collected value and the X, Y, and Z axis acceleration value, in units *g*, see Figure 3.4; AM Data. Sampling frequency was selected to ensure appropriate capture of human movement features but to limit extraneous oversampling and power/memory consumption. Evidencing the choice of 40Hz is the knowledge that basic human ambulation occurs within 0-3Hz (a single leg may heel-strike thrice per second) while components of gait, i.e. muscle activations or center of mass undulation occur at higher frequencies. It is noted that 99% of gait energy is contained below 15Hz and that the majority of components occur below 20Hz [50]. A rate of 40Hz, which is supported in other similar studies, satisfies efficient data capture while minimizing power cost [38] [40].

3.3 Algorithm Overview

The developed algorithm is known as a decision tree scheme, an extension of a RB algorithm. The decision tree scheme follows an intuitive pathway (tree) through checkpoints which guide an input object – in this case a region of target data – through various branches to a certain output. Figure 3.2 depicts this architecture, with arrows indicating decision criteria eventually settling on a final state. One note about nomenclature: categorization describes the process of distilling a larger series down into finer categories – a wholesome viewpoint, whereas characterization involves using specific characteristics of a region to resolve an output. Simply, categorization takes a

Since human gait, posture, and behavior is so diverse, general forms (or models) of particular behavior domains, deemed "schemas", are developed that consider experimental, observable, and intuitive features in their formation. Schemas generally describe the subject's behavior, i.e. *Inverted*, *Lying*, *Sitting*, *Standing*, *Walking*, etc. based on the AM data collected at the prosthetic. The schema developed for this algorithm attempt to span a wide breadth of behavior. This is described in more detail in CHAPTER 6: FUTURE WORK AND CONCLUDING THOUGHTS.

An accurate series describing user behavior as it progresses over time is the intended output of the algorithm. Subject sessions are broken into data regions based on region features. These data sections are not limited to a set duration as in other studies, but because of the algorithm architecture are free to take any duration which best defines the region. To produce such an output the algorithm first calculates four global accelerometry data features. Second, it sorts regions into mutually exclusive Active, Passive, and Transitioning classes based on these features. Third,

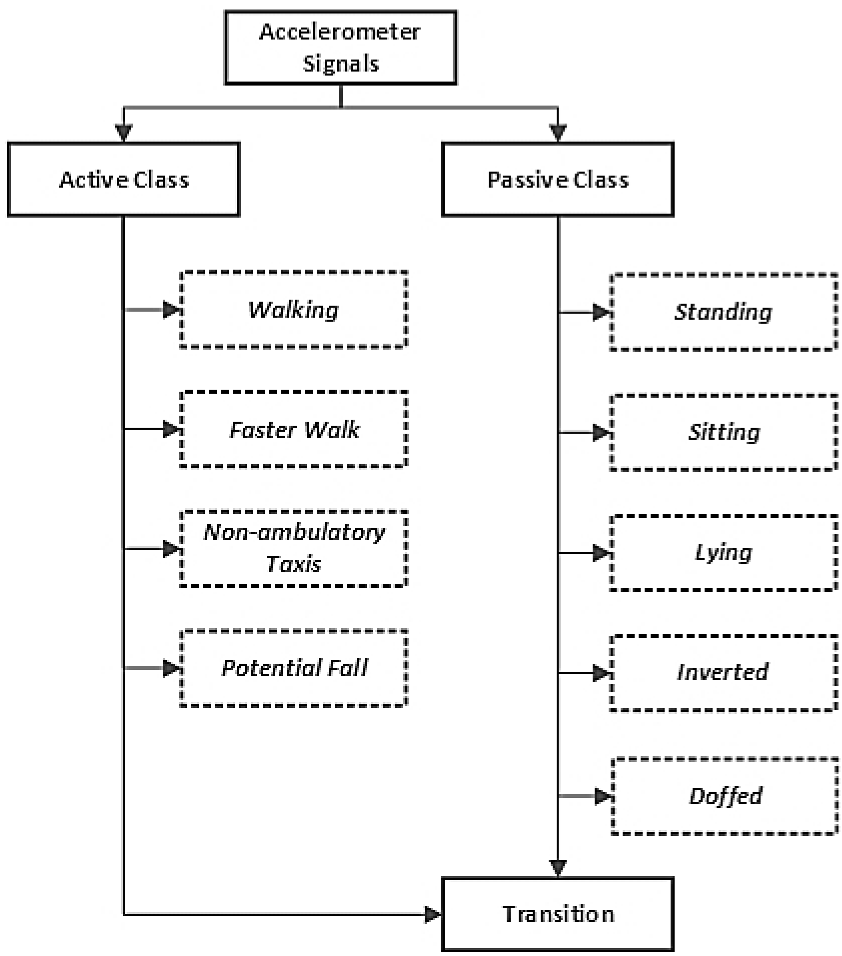

Figure 3.2 Algorithm skeletal categorization schematic.

within these classes regions are characterized, generating schemas estimates. Last, the algorithm's schema output is further processed to appropriately note transitions, allow smooth behavior flow, and to diagnose unclassified regions. Algorithm processing time varies with data file size and computer specifications, but is tolerable in clinical or research settings.

3.4 Behavior Categorization Features

The objective of the four accelerometry features is to extract an efficient number of analysis metrics which can be used to accurately differentiate signal regions into algorithm classes and subsequent schemas. Data features represent a global analysis of the accelerometry data, see Figure 3.3 and Figure 3.4; *Features*, as opposed to real-time differentiation based in windowed analysis.

The first feature calculated is deemed the angular feature, see Figure 3.3; *top*. The AM can function as both an inclinometer during passive behavior (staticity) and as a dynamic activity frequency counter. During staticity, there are three angles to consider; flexion/extension of the leg in the Sagittal plane, abduction/adduction of the leg in the Coronal plane, and internal/external rotation of the leg in the Axial plane. These rotations in a plane can be thought of in relation to the common vessel terminology, pitch, yaw, and roll, respectively, see Figure 3.1. Each angle at time *i* is calculated through trigonometry of the accelerometer channels, i.e.

$$A.Sag_i = cos^{-1}\left(\frac{X_i}{SMV_i}\right) \tag{1}$$

where $SMV_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2}$ [37]. These angle time series are smoothed using a median filter ("MF") of $n = 3$ to remove abnormal spikes [37]. This smoothing frame was intuitively selected so as to smooth over outlier artifacts but not interfere with gross static angular artifacts or dampen the cyclic artifacts of dynamic angular activity. Linear interpolation fills any voids created through

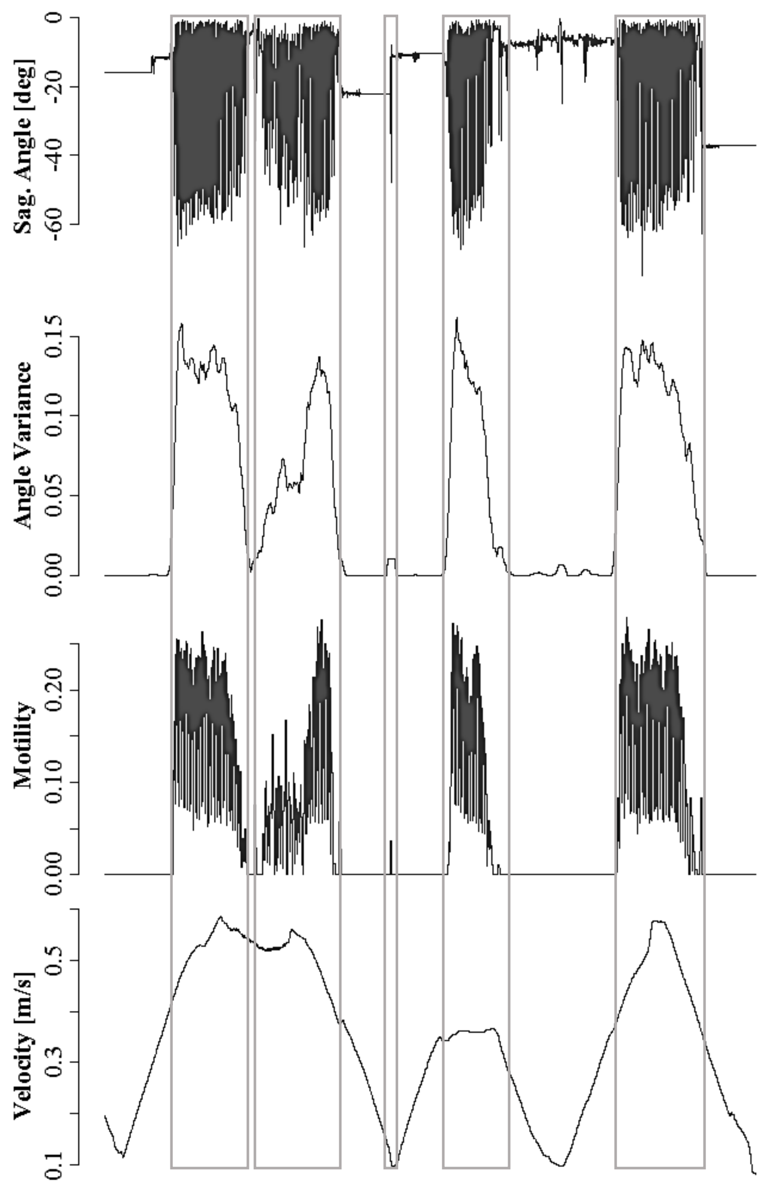

Figure 3.3 Features of the AM accelerometry data. TOP: Angular, exemplified by the Sagittal angle. TOP MIDDLE: Angular Variance. BOTTOM MIDDLE: Motility. BOTTOM: Velocity. Boxed *regions represent ACTIVE regions.*

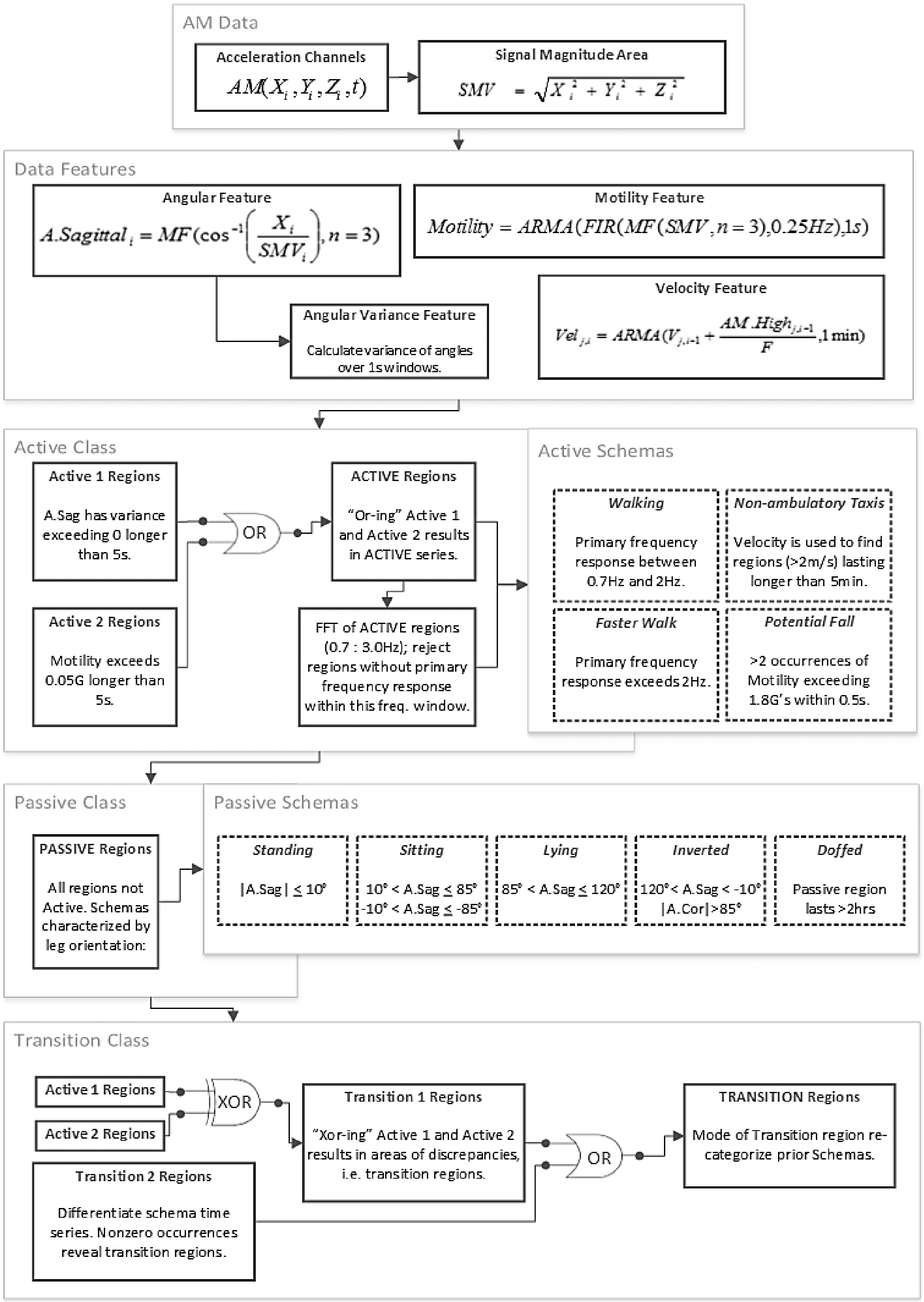

Figure 3.4 Algorithm decision tree schematic. ActiGraph data consists of three acceleration channels and a timestamp (AM Data). Global accelerometry features are calculated (Features). The active class consists of angular variance, motility, and velocity feature analysis. The Passive Class examines the static inclination of the leg to characterize behavior. Transitions are calculated last, considering regions of active classification discrepancies and local schema categorization variation.

computation error over the trial. Angles are defined as deviations from the downward gravitational axis, i.e. if mounted and initialized correctly, then a standing subject produces a sagittal and coronal (pitch and yaw) leg orientation angle of 0° (see Figure 3.6 for how this structure characterizes passive behaviors).

Angular variance is the second feature calculated before categorization and describes, as implied, the spread of a region of angular data, see Figure 3.3; *top middle*. As variance (sometimes called the second central moment) is a distance measurement of a particular value from the mean of a collection of values, this feature is a product of a progressive windowed process:

$$m_k = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^k \tag{2}$$

where n is the sample size, i is the array index, $\bar{x}$ is the window mean, and k is the moment order, 2. m_2 is calculated over 1s windows in this algorithm. This duration is selected so as to capture activity variations within this timeframe, knowing 0.8s-1.4s windowing durations are optimal in human activity analysis [39]. Variance is calculated for each angular feature; Sagittal, Coronal, and Axial, and a gross measure of windowed variance is gathered by adding these series in quadrature over the entire data session, creating a global variance series.

The third feature is motility, a measure of activity intensity, see Figure 3.3; *bottom middle*. Raw acceleration signals contain three components: bodily accelerations, gravitational accelerations, and noise. The AM measures a linear combination of these accelerations which overlap both in the time and frequency domain. The consequences of noise are limited in the installation, circuitry, and processing and are considered inconsequential. A MF is applied to the raw X, Y, and Z accelerometry arrays ($n = 3$) to remove abnormal spikes and the SMV is calculated by adding these in quadrature, similar to the angular process. Frequency filtering produces an acceptable approximation of both bodily and gravitational components, and so a high-pass Finite Impulse Response Filter ("FIR", from 0.25Hz) is utilized to differentiate the gravity and body signals [50] [36]. Applying this to the SMV produces a high-pass SMV series. This is finally smoothed using an Autoregressive Moving Average ("ARMA") filter considering 1s windows. The final Motility feature then is described as:

$$Motility = ARMA(FIR(MF(SMV, n = 3), 0.25Hz), 1s) \tag{3}$$

Motility values range between 0g and 8g's, but typical behavior remains below 1.5g's.

Velocity is the final calculated feature, where an iterative kinematic scheme is utilized on each channel to find the velocity component on that axis at that instant, see Figure 3.3; *bottom*. From the kinematic equation

$$V_t = V_{t-1} + a_{t-1}\Delta t,$$

an iterative scheme is devised;

$$V_{j,i} = V_{j,i-1} + \frac{AM.High_{j,i-1}}{F} \tag{4}$$

Here, Eq. (4) describes the linear velocity of channel *j* at time *i*. *AM.High* is the high-pass filtered X, Y, or Z channel subject to the same FIR as above, and *F* is the sampling frequency. This feature is useful primarily in determining non-ambulatory taxis, so the resultant velocity is calculated by adding the time series components, $j \in [1:3]$, in quadrature and smoothing with an ARMA filter considering 1min windows.

These four accelerometry features allow for efficient encoding of the differences between characterized schemas. This is neither a comprehensive nor a perfected feature list (smoothing and filtering parameters can be altered and more features could be added/subtracted), but the application of these calculated features proves accurate and robust enough with limited computations.

3.5 Behavior Categorization Classes and Schema

The algorithm decision tree scheme sorts behavior into three classes based on the features just described: active behavior, passive behavior, and the transitional regions between behaviors. Within these classes, detailed characterization decomposes regions down to behavioral schemas. This algorithm considers nine possible schemas: *Doffed*, *Inverted*, *Lying*, *Sitting*, *Standing*, *Walking*, *Running*, *Fast*, and a catch-all, *Other*.

Schema names are intended to be self-explanatory and intuitive. A *Doffed* schema indicates that the prosthesis is not in use and is detached from the user. The passive orientation schemas (*Inverted*, *Lying*, *Sitting*, and *Standing*) are characterized by the angle of the leg and are described soon. *Walking* and *Running* are active schema differentiated by the region's periodicity. Note: the *Running* schema name is meant to indicate an increase in stride frequency, not typical running locomotion. The *Fast* schema is indicative of non-ambulatory taxis. The schema category *Other* labels any region in time which is unclassifiable.

The algorithm first locates the active regions of a data session via two metrics, see Figure 3.4; *Active Class*. Active regions are identified first because of their periodicity and/or high intensity characteristic features. In one pathway, deemed *Active 1,* motility regions exceeding a threshold for more than 1s are deemed active. This metric serves to capture any intense signal regions with high sensitivity. In the other pathway, *Active 2*, regions of sagittal angle variance exceeding a low threshold for more than 5s are deemed active. This metric serves to record more angular-specific activity regions. These two arrays consist of binary time waves that are binary high (1) when their criteria are met and low (0) when they are not. The arrays are then superimposed via "or-ing" into a final *ACTIVE* binary array, i.e.

Table 3.2 "Or-ing" mechanism.

Active 1	*Active 2*	*ACTIVE*
0	0	0
1	0	1
0	1	1
1	1	1

The high regions are deemed active (or dynamic) in the *ACTIVE* array.

Within the active class, schemas to be characterized are either *Walking*, *Running* (a faster cyclic behavior), or non-ambulatory taxis; *Fast*. The velocity feature is assessed for regions exceeding 2m/s for longer than 5min for the *Fast* schema characterization. These regions are characterized as non-ambulatory locomotion, i.e. driving or cycling. To differentiate between *Walking* and *Running*, a FFT is calculated over individual active regions to analyze the frequency spectrum. Frequencies outside of a 0.7Hz - 3.0Hz range are ignored [38], and the FFT shape within this frequency window is assessed for acceptable position of maximum frequency response and an adequate number of observations. The most responsive frequency is deemed the cyclicity frequency of the region, see Figure 3.5. The *Walking* schema category is set below 2Hz, while fast walks and runs lie above this value. Areas in this class where the *Active 1* or *Active 2* criterion are not satisfied or where the FFT is rejected are deemed inactive, i.e. passive or transitive and are subsequently processed.

The algorithm then considers passive (static) behaviors, see Figure 3.4; *Passive Class*. Outside of the active regions the AM functions as a reliable inclinometer, where the angular feature is utilized to characterize behavior. Specifically, the sagittal and coronal angles of the leg are used to differentiate between the possible passive schema estimates. In this algorithm, *Standing*, *Sitting*, *Lying*, and *Inverted* comprise the schema options of the passive class. Periods between active regions are assessed, capturing passive prosthesis orientation arrays from the angular feature (these arrays are used later to test orientation populations). From each of these regions the median

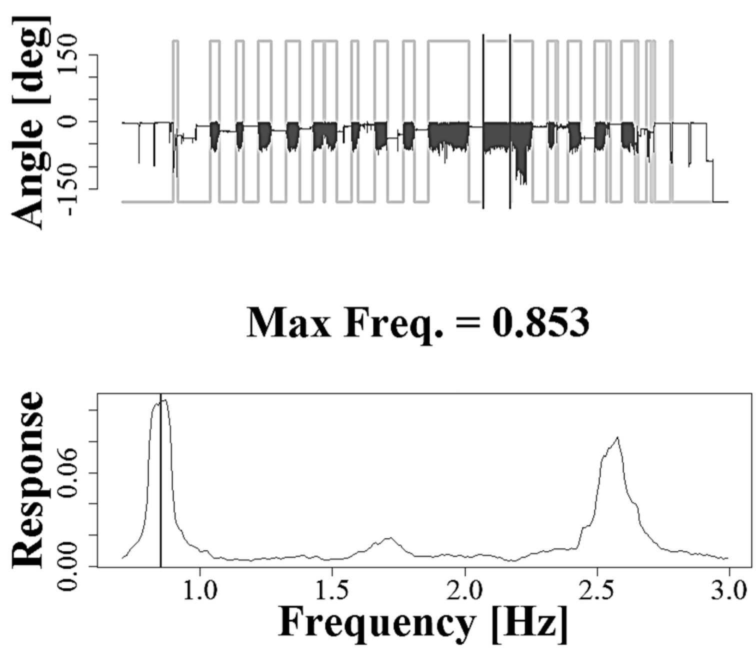

Figure 3.5 TOP: Barred active region of sagittal angular feature is subjected to a FFT. BOTTOM: the highest response frequency is selected (vertical line).

orientation angle is found, representative of the region's orientation, and a schema is assigned according to the following rule:

$$\begin{cases} Sitting, & -85° \le A.Sag_i < -10° \\ & or\ 10° < A.Sag_i \le 85° \\ Standing, & |A.Sag_i| \le 10° \\ Lying, & 85° < A.Sag_i \le 120° \\ Inverted, & 120° < A.Sag_i < -10° \\ & or\ |A.Cor_i| > 85° \end{cases} \tag{5}$$

Because passive angular feature arrays sometimes drift and are not normally distributed, the median is utilized as opposed to the mean or an indexed assessment of orientation via Eq. (5) (see Figure 3.6 for a graphical display of Eq. (5)). It has been determined that a passive leg orientation over 20° is sitting (typically up to 60°), less than 10°is usually standing, while orientations between

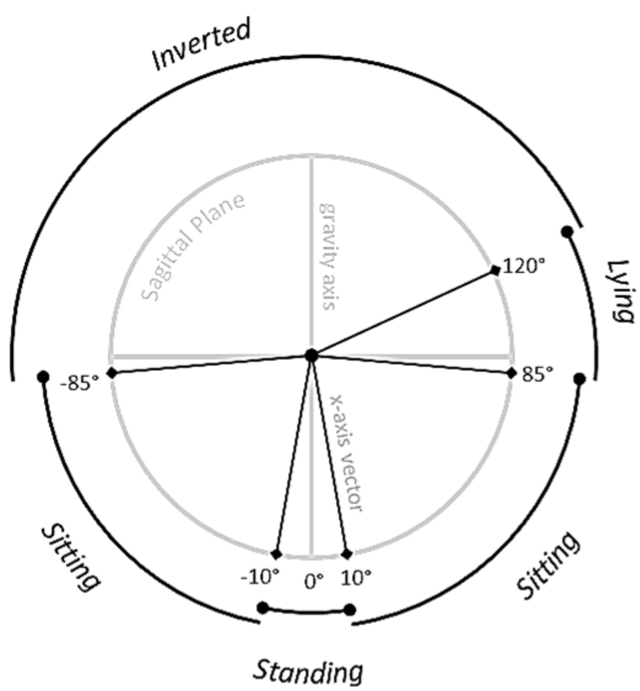

Figure 3.6 Characterization of postural sagittal orientation of a passive leg. The light circle represents the possible rotations of the leg on the sagittal plane and the dark lines - the x-axis vector - border the distinctions between passive schemas characterized in Eq. (5). Dotted arc ends indicate inclusive possession of the angle.

10° and 20° encodes either sitting or standing [38]. The differentiation between sitting and standing in this regime is a prominent challenge to behavior classifiers.

It is important to note that categorization into schemas has followed mutually exclusive criteria; an active region excludes it from being passive and all schema categories within the classes do not allow for any overlap by virtue of the characterization structure. It is at this point that the algorithm considers other categories which are disassociated from the active or passive classes. These possible schemas outweigh any prior categorizations and can write over schemas from the active or passive classes.

Considered at this stage are *Doff*s and *Potential Fall*s. Doffing the prosthesis is architecturally grouped within the passive class. As there is difficulty differentiating between a doffed prosthesis or static stance, the *Doffed* schema is characterized by the absence of any activity for some time threshold, currently 2hrs. Again, this is a superior categorization, and any regions are overwritten if they fall under this criterion. The *Potential Falls* schema is discussed more in CHAPTER 6:FUTURE WORK AND CONCLUDING THOUGHTS. It is based on previous studies and analyzes the Motility feature for consecutive spikes above a certain threshold within a certain timing window. If such is found, this window is categorized under this schema.

The third class, transitions, is now processed, see Figure 3.4; *Transition Class*, which considers the points in time between the exchange from active to passive classes and the regions of schema transitions within a class. Like the active class, the transition class is a composition of two criteria pathways. In the first, *Transition 1*, transitions are found through “xor-ing” (exclusive or-ing) the *Active 1* and *Active 2* arrays such that temporal differences are found. This mechanism is presented in Table 3.3. This mechanism simply finds when the two arrays do not agree. These discrepant transition regions represent periods of high angle variance or motility that have not settled into either a passive or active class. *Active 1* and *Active 2* arrays are commonly overlapping and it is rare to identify a large region as transitional in this pathway.

Table 3.3 "Xor-ing" mechanism

Active 1	*Active 2*	*Transition 1*
0	0	0
1	0	1
0	1	1
1	1	0

In the second pathway, *Transition* 2, the Schema series is differentiated in time (each categorical schema option has a designated numeric value; values of 5 represent *Walking* behavior, 4 represent *Standing*, and 3 – 1 are *Sitting*, *Lying*, and *Inverted*, respectively, and 0 is *Other*). Nonzero regions are deemed transitional and are recorded in the *Transition 2* pathway.

The *Transition 1* and *Transition 2* arrays consist of binary time waves that are high when their criterion are met. These arrays are then superimposed via "or-ing" (see Table 3.2) into a final binary array, as in the active class above. High values are deemed *in Transition*. Transition regions are assessed for their probable schema composition via linear (behavior) interpolation and smoothed to accommodate appropriate behavior. The *In Transition* schema is not utilized directly in data analysis as this category exists primarily for interpretation clarity. From this point, all schemas have been assigned and the algorithm is concluded.

Figure 3.7 presents the transition class mechanism and how this schema estimate is imposed on a session behavior time series. At top is an example of a complex sagittal angle feature. Initially, the session has an unknown category and has no region specificity (series 1). After proceeding through the active (A) and passive (P) classes, regions have been identified (series 2), with some regions not qualifying (?). Schema characterization then takes place (series 3), and estimates are imposed on known regions. Here, *Sitting* (Sit), *Walking* (Walking), and *Standing* (Stand, N), estimates have been imposed. In series 4 the transition class is imposed, finding where Active 1 and Active 2 sub-class arrays disagree and where schemas transition (T, stripes). Finally, schema estimates are realistically interpolated within transition regions, resolving intermittent behaviors (series 5).

3.6 Algorithm Output

User activity through time is the most direct and consequential output of this algorithm. Beyond this, various other clinical and academic features and relationships can be analyzed. For instance,

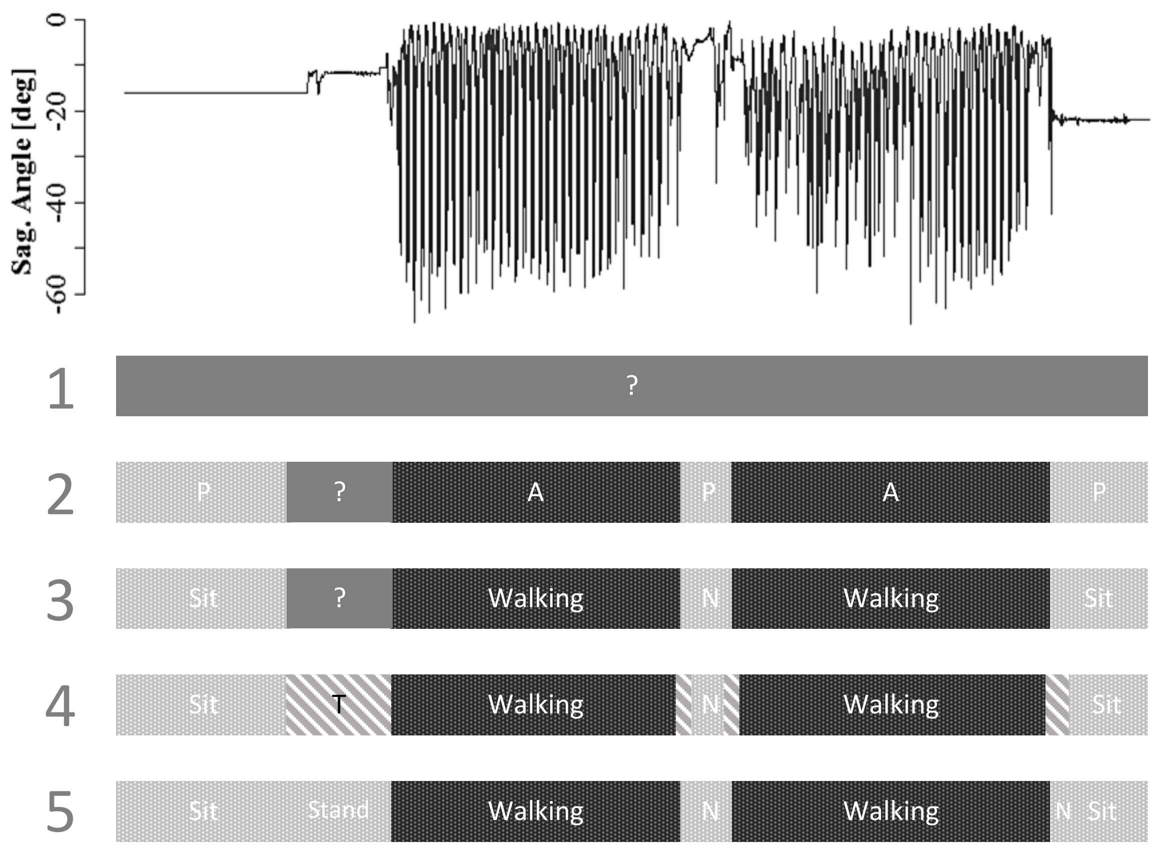

Figure 3.7 Transition class mechanism schematic.

all transitions between schemas can be assessed for frequency, direction, and when in time they occur. Total duration as well as regional duration in schemas can be captured. The temporal series of passive angular orientation can be analyzed, as can the series of cyclic frequency. Results and implications of the algorithm are presented in the following chapters.

CHAPTER 4: RESULTS

The results of this behavior categorization algorithm are henceforth presented. Eleven trials are included in the validation of this classifier. Behavior categorization and the resulting practical data output are included in this discussion. The intricacies of output validation are discussed, though interpretations of results and other output can be found in CHAPTER 5: DISCUSSION.

4.1 Behavior Time Series Results

Eleven behavior time series were generated by the algorithm, one for each subject trial (see Figure 4.1, TOP for an example), and were compared to a log of discrete ground truth activity that was charted during the trial study. GTD consisted of noting the onset of subject sitting, standing, walking, and other activity such as donning/doffing or traversing stairs. As the algorithm can classify stands, sits, and walks it were these activities which were used in the validation (stairs were included as a subject walk). The generated behavior was said to be correct when GTD was clearly in correspondence with said generated time series.

Categorization results are presented in Table 4.1. The table presents the overall categorization effectiveness, the effectiveness in differentiating active and passive regions, and the effectiveness in identifying a subject sit, stand, and walk.

For overall effectiveness, GTD were iteratively graded against the algorithm output. The algorithm was correct in this regard with accuracy 92.02%. For effectiveness in active or passive differentiation, GTD were again iteratively graded, where a subject sit or stand were classified as passive and walks as active. In this the algorithm was correct with an accuracy of 100.00%. In classifying the individual behavior, GTD were iteratively compared to algorithm schema estimates. In this, subject sits were identified with accuracy 82.69%, stands at 92.42%, and walks at 100.00%.

Table 4.1 Behavior time series results.

Subject	**Effectiveness Overall**	**Effectiveness Active/Passive**	***Sit***	***Stand***	***Walk***
1	84.85	100.00	58.33	100.00	100.00
2	100.00	100.00	100.00	100.00	100.00
3	100.00	100.00	100.00	100.00	100.00
4	100.00	100.00	100.00	100.00	100.00
5	97.06	100.00	91.67	100.00	100.00
6	72.73	100.00	33.33	75.00	100.00
7	89.47	100.00	100.00	66.67	100.00
8	87.18	100.00	80.00	75.00	100.00
9	83.87	100.00	54.55	100.00	100.00
10	97.06	100.00	91.67	100.00	100.00
11	100.00	100.00	100.00	100.00	100.00
Overall	**92.02%**	**100.00%**	**82.69%**	**92.42%**	**100.00%**

4.2 Other Useful Results

Within the structure of the algorithm, certain analyses are performed which hold some potential utility. Again, these output results of the algorithm are presented here and discussed later.

Created in characterizing passive schema, the passive prosthesis orientation arrays offer insight into the duration and angle at which a subject is inactive. These can be compared, as three are collected with respect to the three angle planes of the system. Another useful analysis in the algorithm is an inspection of transitions between schemas. Here, the behavior time series is scanned and memory of how schemas change is recorded. A *Transition Matrix* is generated which presents the number of transition occurrences between schema and the net duration the subject was within that schema (in percentage).

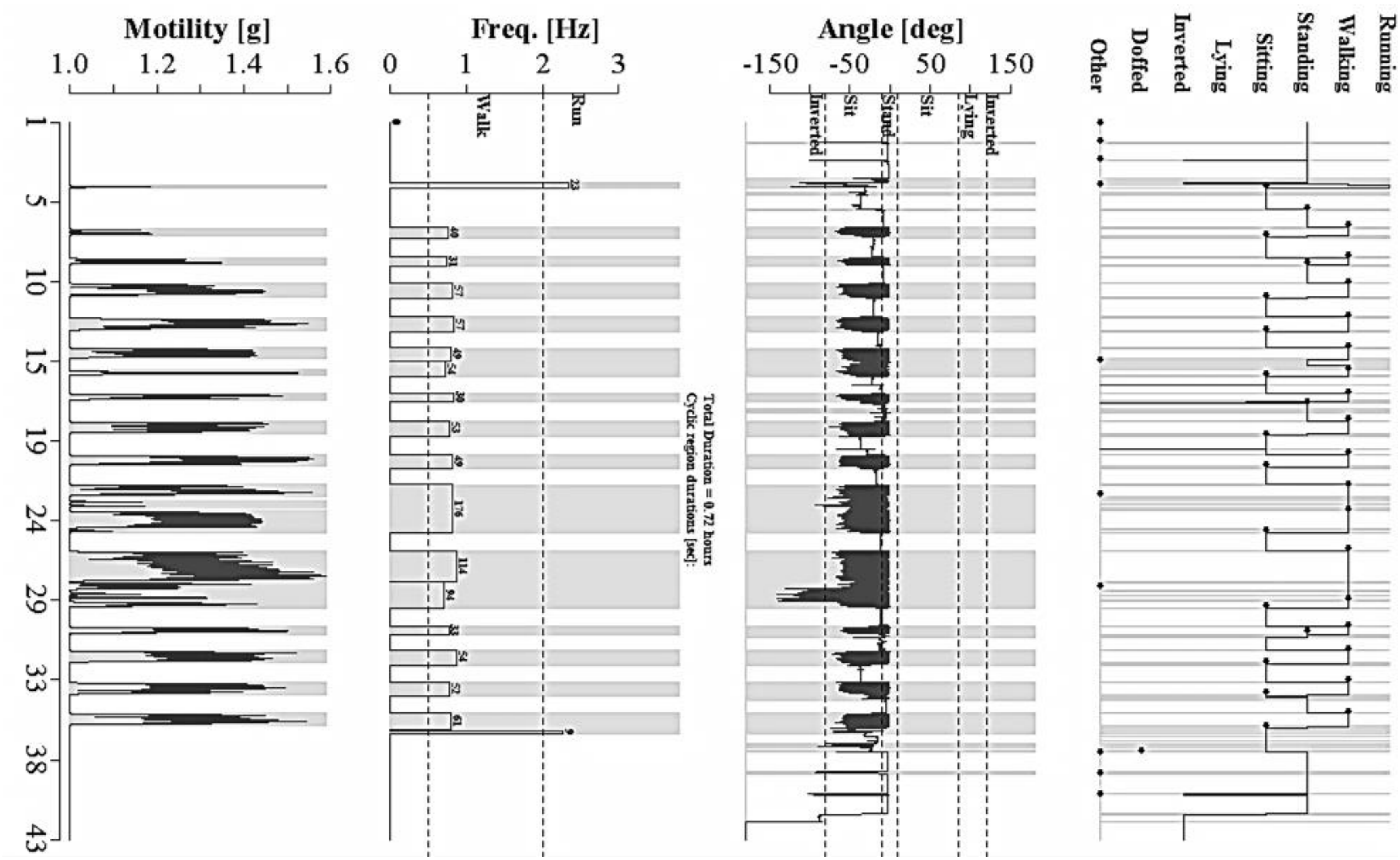

Figure 4.1 Algorithm behavior output vs. time [min]. TOP: Behavior time series estimates with schema options presented at left. Algorithm decisions roll out in time (solid line). GTD are imposed over algorithm behavior estimate (dot). Transition regions are outlined (vertical shading). TOP MIDDLE: Sagittal angle time series. Active 2 regions are highlighted (vertical shading) and schema boundaries are defined (dotted line). BOTTOM MIDDLE: Frequency of cyclic active regions. Duration (in seconds) is displayed atop bar. Walk and Run schema boundaries are displayed (dotted line). BOTTOM: Motility feature. Active 1 regions are highlighted (vertical shading). In this data session, the prosthesis was donned at minute 4 and doffed at minute 36.

CHAPTER 5: DISCUSSION

The algorithm output is well within acceptable physical agreement for most of its measured metrics and, most importantly, presents reasonable results which are useful and easily interpretable within a clinical or research setting. In this chapter, output and results of the algorithm are explained for their utility to research and health care. Validation of output is also provided and discussed. A section on validation efficacy and standards is included. As in CHAPTER 4: *RESULTS*, the behavior time series and its validation will be the first focus, and then secondary outputs will be interpreted. Finally, expansions on algorithm decisions and mechanisms are presented.

5.1 Interpretation of Behavior Time Series

The algorithm's agreement with GTD and physical expectations is impressive and promising. An overall effectiveness of physical behavior agreement at 92.02% over eleven subjects with around 40 ground truth classified activities per subject is indicative of its robustness to human variance and sensitivity to behavior. Perfect effectiveness differentiating active and passive activity is also a hugely supportive result as well, though not entirely unexpected.

An effort has been made to simplify the interpretation of the algorithm's main output. The behavior time series is meant to be a reference for understanding a subject's activity as her day progresses using the instrumented prosthesis. Reading such a plot should be straightforward. Figure 4.1; TOP presents an example from the study (with superimposed GTD dots for validation), demonstrating the intuitive implications of the output. Behavior flows sensibly through schemas, while transition highlights (vertical highlights, TOP) add a sense of confidence to the algorithm's decision. Transition regions, as previously stated in section *3.5 Behavior Categorization Classes*, are assessed to best suit a smooth transition through schemas but do not always encode for real behavior perfectly. And as such, transition regions should be considered with lower confidence. A final note about transitions; the behavior series is designed to accommodate a reasonable flow between schemas, and so transition regions may appear to flow from *Walking* to *Sitting* but typically include a small *Standing* region, for example, which might not be visible on the viewed time scale.

Algorithm schemas are intended to be intuitive, as each are designed to characterize a behavior/activity that suits their namesake. The *Running* schema exists to characterize cyclic behavior with a principle frequency response exceeding 2Hz. It is not literally suggestive of a running subject in the traditional locomotion sense, but only a “faster moving” subject. The *Other* schema category is a catch-all for data regions which are not active, do not qualify as passive, and aren’t captured by other schema categories (*Fall, Doffed,* etc.). These *Other* regions are sometimes very atypical transition periods, very atypical active regions, areas of abnormal signal noise, or possibly a bad installation is to blame.

The behavior schema time series presents the algorithm reader with a straightforward interpretation of user activity over the session. Trends in behavior are displayed as well as the duration in that behavior. The array of schemas offered to the user allows for a comprehensive understanding of prosthesis use and subject behavior. From this, interpretations on prosthesis effectiveness, relating to comfort, fit, or confidence, can be gleaned. For instance, after what activity is the prosthesis most often doffed and for how long, or how often does the subject sit after high activity? A prosthetist or researcher can examine the behavior time series and assess how best to suit a prosthesis treatment (fit or components) to the individual. They might also recommend how best to suit the individual's activity to maximize comfort (i.e. when to doff), or might have a conversation with the user about prosthesis confidence when examining a particular time region.

5.1.1 Interpretation of Behavior Time Series Validation

The validation study results of eleven subjects are presented in Table 4.1. The main confidence of the algorithm must be placed in overall effectiveness, as this is a direct comparison between ground truth subject activity (GTD) and the algorithm schema decisions. Overall categorization effectiveness is found to be 92.02%, though this accuracy might be a misleading value if not interpreted correctly.

GTD are presented in discreet instances (with unknown human accuracy), and because of this we are unable to appropriately compare the algorithm's decided duration in a schema to a GTD activity. Had GTD been represented by a continuous classified activity series, duration as well as behavior could have been compared. As such, a discrete-to-continuous comparison must be made, and so if the algorithm had disagreed with GTD but soon transitioned to the correct GTD activity, the discretized data results in inaccuracy while continuous GTD would have found the algorithm agreeable for a portion before the next activity comparison. The form of the GTD then inhibits the comparison of activity weighted by activity duration, which is liable to improve overall results as observed in other high accuracy AM studies.

There are also hidden variables associated with our subject pool which assuredly contribute in some manner to the effectiveness of the categorization algorithm. These factors, such as physical characteristics of subjects like age, height, weight, or others like state of mind, fatigue, or fitness, inherently play a role in the behavior, activity, physiology, and attitude of the subject, effecting results. For instance, subject #6 scored markedly lowest in categorization effectiveness overall (72.73%, with the algorithm soaring to 94% effectiveness overall without this data point) but is also the lightest and youngest subject in the group by far (48.3kg vs 92.8kg on average and 29yrs vs 50yrs on average). Could the activity of younger or lighter, more agile individuals contrast with heavier, more deliberate seniors in such a way that it is difficult to categorize? Examination studies like this and others are mentioned in CHAPTER 6: FUTURE WORK AND CONCLUDING THOUGHTS.

In probing the validation study effectiveness overall subject scoring statistics, an interesting discretized presentation was observed. Figure 5.1 demonstrates the distinct groupings in the presentation of overall effectiveness – with some subjects categorized very true to GTD, a

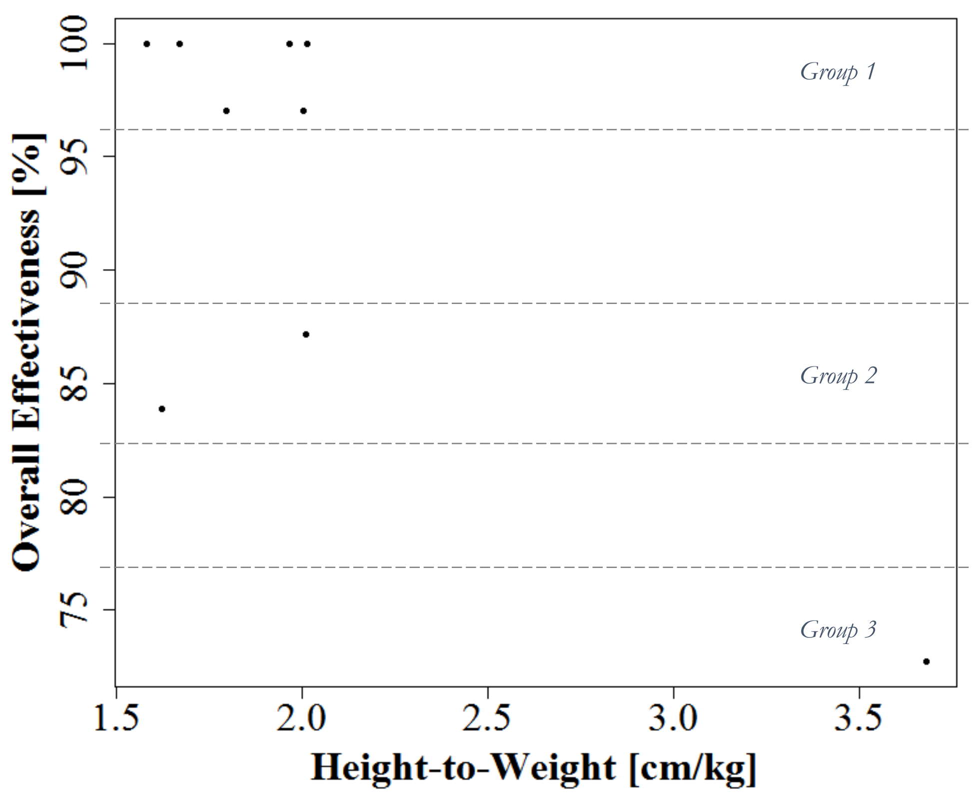

Figure 5.1 Algorithm effectiveness overall might be modulated by subject anatomy.

few scored reasonably well, and one far worse – and the relationship with subject height-to-weight ratio (lacking two subjects' anatomical data). The presentation is suggestive of levels separating the evaluated subjects through some factor effect. Intuition suggests that the effectiveness of the algorithm's categorization will distribute normally, but there are possibly strong factors which skew this distribution, with Figure 5.1 evidencing that subject height-to-weight ratio is one of those strong factors. As previously stated, further evaluations will be needed to identify and tune the algorithm to these factors.

The differentiation between active and passive behavior accuracy (100.00%) is unremarkable and experienced in other studies [40]. The form of accelerometer data generated by cyclic activity is responsive to categorization, allowing for high identification accuracy. As this algorithm is not simply an active/inactive classifier, the individual schema differentiation accuracy is of high importance. A discussion regarding the accuracy differentiating between passive schemas follows.

5.1.2 Sitting & Standing Accuracy

It is obvious that the algorithm's RB scheme finds the accurate differentiation between a sitting and standing subject difficult, as these two schema, while together grouped in the passive class are properly identified 100.00% of the time, separately were identified with 82.69% and 92.42% accuracy, respectively. The mechanism for differentiation, while allowing for disjoint categories, fails at appropriately characterizing passive orientation data regions and is a plague to activity classifiers [37] [40]. For instance, imagine a typical leg or lower limb prosthesis without seeing any body segments above the knee. From solely this vantage it would be difficult to differentiate if the body was sitting or standing, as the lower limb retains overlapping vertical orientations in both of these postures. In an analysis of the eleven subject data posture distributions, it is observed that the populations of discrete leg orientation measurements in sits and stands often do present as independent from one another (see Figure 5.2 for an example). A statistical battery of tests for each subject support this claim, see Table 5.1. In these tests, regions of sits and stands were identified for each subject and the representative median value are collected (from the passive prosthesis orientation array). Each collection was tested for normalcy. The number of sits and stands, *N*, are

Table 5.1 Subject Sit and Stand population statistics. Highlighted cells indicate significant normal distributions.

Subject	**Posture**	**N**	**Significant Normalcy**	**Wilcoxon rank sum test with continuity correction**	**Kruskal-Wallis rank sum test** X^2	**Kruskal-Wallis rank sum test** p-value
1	Sits	9	$p \ll 0.01$	$p \ll 0.01$	46.4	$p \ll 0.01$
	Stands	21	$p = 0.081$			
2	Sits	28	$p = 0.266$	$p \ll 0.01$	70.8	$p \ll 0.01$
	Stands	18	$p = 0.117$			
3	Sits	23	$p = 0.110$	$p \ll 0.01$	51.1	$p \ll 0.01$
	Stands	10	$p = 0.118$			
4	Sits	39	$p = 0.001$	...	85.8	...
	Stands	16	$p = 0.009$			
5	Sits	24	$p = 0.051$	...	57.0	...
	Stands	13	$p \ll 0.01$			
6	Sits	12	$p = 0.013$	...	44.3	...
	Stands	17	$p \ll 0.01$			
7	Sits	27	$p = 0.001$	...	70.7	...
	Stands	19	$p = 0.142$			
8	Sits	25	$p = 0.031$	...	57.2	...
	Stands	12	$p = 0.005$			
9	Sits	20	$p = 0.070$	...	58.1	...
	Stands	18	$p = 0.017$			
10	Sits	14	$p = 0.018$	...	42.6	...
	Stands	14	$p = 0.005$			
11	Sits	18	$p = 0.034$	...	48.9	...
	Stands	14	$p = 0.350$			

represented for each subject. Because of the mix of normal and non-normal distributions and nature of the data sets, two non-parametric tests were selected to analyze data. Sits were found to be significantly different than stands for each subject via the two non-parametric tests: a Wilcoxon rank sum test with continuity correction examining the null hypothesis that two samples come from the same population, and a Kruskal-Wallis rank sum test examining the null test that samples hold equal variance (data were stacked and differentiated into "sit" and "stand" factors). All null hypothesis were rejected ($p\ value \ll 0.01$). These results imply that sit and stand postures for

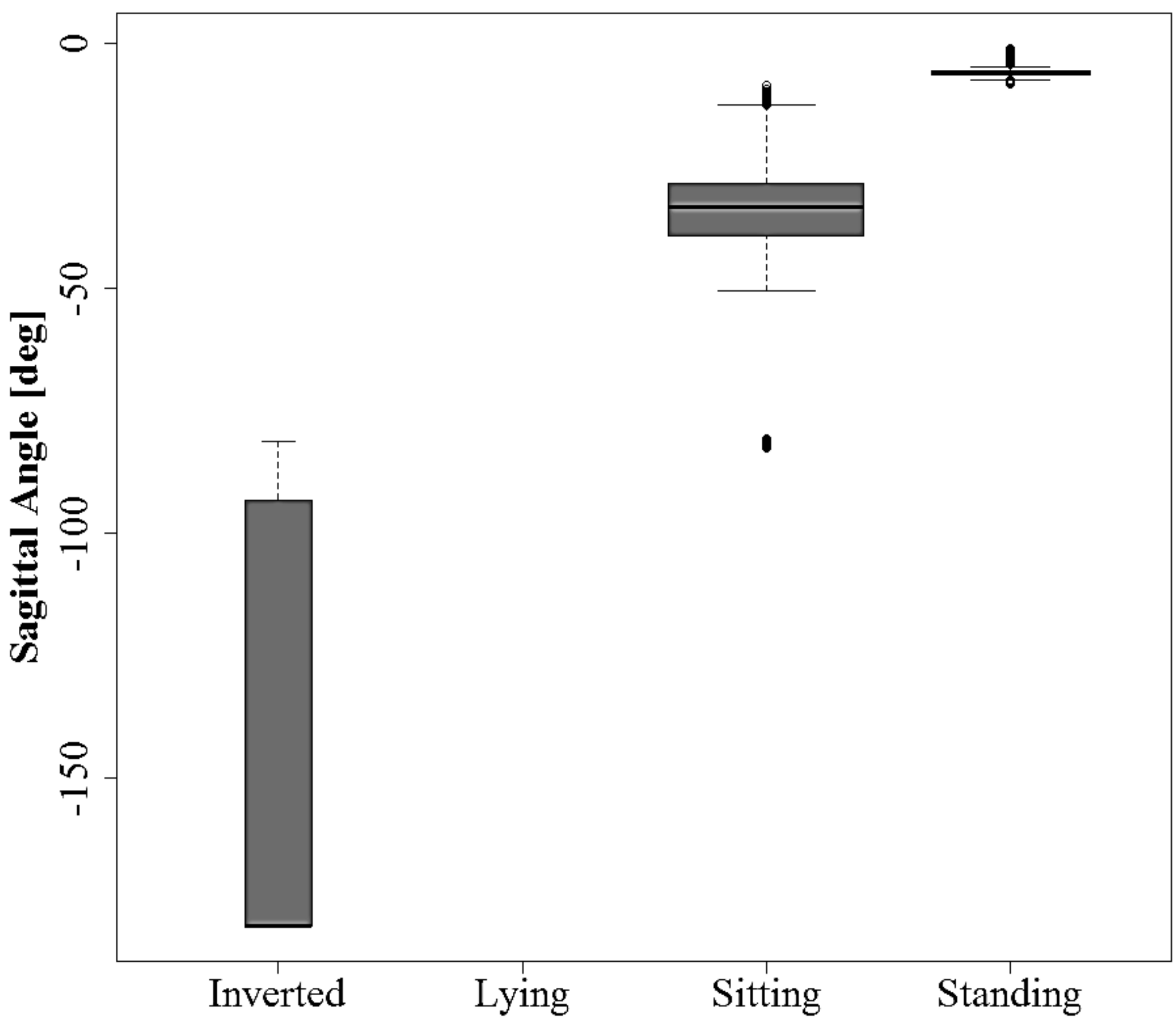

Figure 5.2 Example distribution of subject leg orientation in passive schemas. This subject session did not include any Lying regions. Box width is proportional to the square root of the number of observations in each group.

each individual for this subject population – and by the central limit theorem the general population – are separable based on measurements of the individual's sagittal angle measurements to some significant accuracy.

A pooled analysis of all eleven subjects reveals much about the sensitivity the algorithm must have to differentiate between user sits and stands. For each subject, GTD sit and stand regions were identified and the algorithm's passive sagittal orientation angle was captured. These data were stacked and differentiated into two factors, "sit" and "stand", based on the GTD category. The pooled sit and stand populations were tested for a significant difference between user sit and stand postures. Such a test proves that algorithm categorization is valid and worthwhile. The pooled sit and stand populations were tested and found to be non-normally distributed ($p\ value = 0.000242,\ p\ value = 0.0003324$, respectively, see Figure 5.3). Populations were found to be independent, satisfying the assumption made from the algorithm above (Wilcoxon; $p\ value \ll 0.01$, K-W; $p\ value \ll 0.01, X^2 = 41.85$). From this result validity towards postural differentiation is achieved.

From this analysis, an optimization of characterization thresholds can be implemented. Eq. (5) presents the current criteria for characterization of passive regions based on the passive leg orientation array median value. Subject stands were identified with 92.42% accuracy, and this I believe is due to a nearly fine-tuned characterization window of $10°$ and the narrow region in which the observed subject stand values occupy (82% occurrence between $-15°$ and $0°$ compared to 31% of sits for the same window). An optimization routine was implemented and it was determined that a widening of the stand characterization window to $12°$ will result in increased characterization accuracy. After widening by 2° to either side (a 20% difference), a new algorithm effectiveness was gained. These results are presented in Table 5.2. With the widening comes a sacrifice in acceptable sitting values which is reflected with a *Stand* effectiveness increase to 97.73% and a decrees in *Sitting* effectiveness down to 77.47% while overall effectiveness increased over the original 10° window. Further increases proved insignificant to effectiveness overall. Optimizing in the other direction produced similar results, and so the intuitively chosen

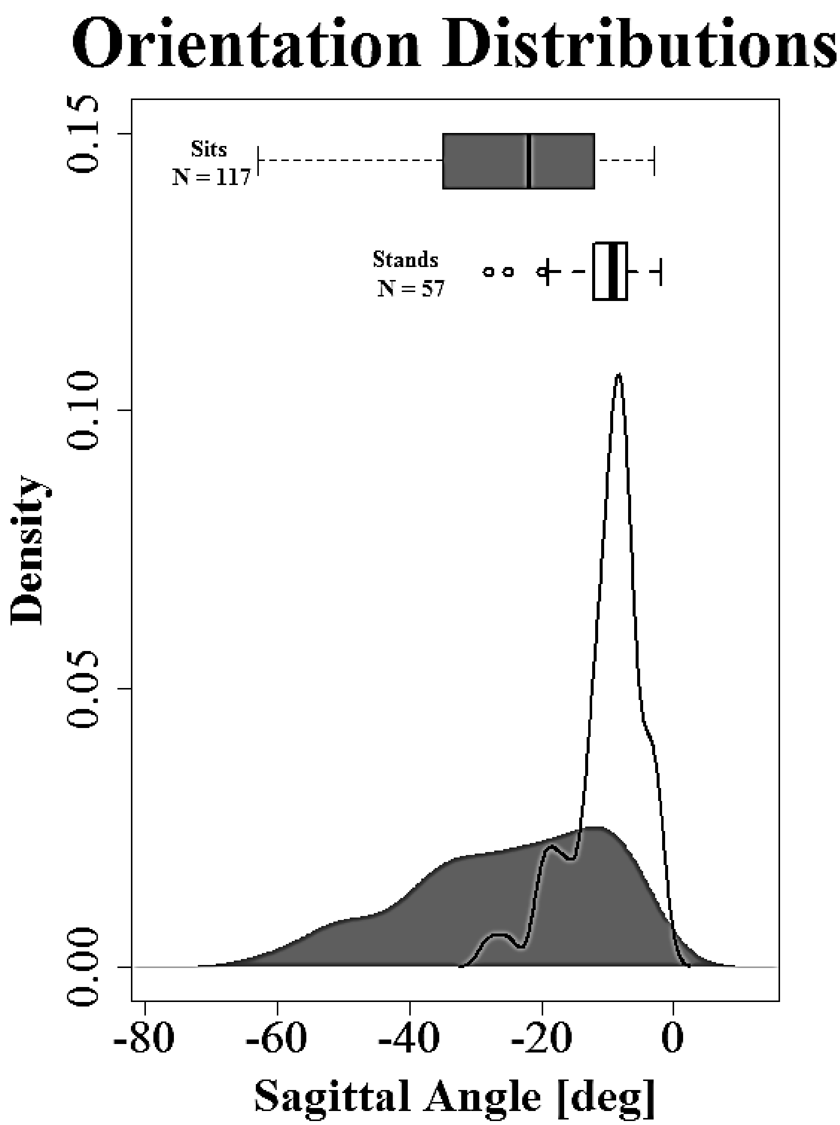

Figure 5.3 Pooled sitting (dark) and standing (light) passive leg orientation density distributions for all subjects. Distributions were non-normal. Distributions are lightly smoothed for interpretation.

10° original window bounds are found to be close to optimal but an augmentation to 12° increases overall accuracy, see Table 5.2 and Figure 5.4.

Table 5.2 Optimized sit/stand parameter results. Original 10° window results are presented (same as Table 4.1) alongside the investigated 8°, 12°, and 14° window results.

	10° Window	**8°Window**	**12° Window**	**14° Window**
Effectiveness Overall	92.02%	91.31%	92.36%	91.10%
Effectiveness Active/Passive	100.00%	100.00%	100.00%	100.00%
Sit	82.69%	83.22%	77.47%	76.05%
Stand	92.42%	91.01%	97.73%	98.79%
Walk	100.00%	100.00%	100.00%	100.00%

In finding that differentiating between sits and stands is slightly optimized with a widened window, it either falls to outside approaches to improve categorization effectiveness or to accept the current algorithm's state. Besides orientation, other studies have analyzed the transition features between behaviors and train classifiers to recognize the current state based on which variety of transition occurred last [36] [40] [37]. Results of such studies vary (typically they are deemed acceptable and good), but are difficult to compare with or apply to this study. Transition identification requires either multiple sensors to capture the orientation relationship between body segments or rigorous signal processing (such as ML schemes). Typically, these studies record well-defined laboratory behavior and train ML algorithms on this, ensuring discernable transitions. Given the approach here – limited instrumentation with a simple and robust daily AM - can we accept things as they are and possibly aim to improve effectiveness via means other than transition identification? These improvements will be discussed in CHAPTER 6: FUTURE WORK AND CONCLUDING THOUGHTS.

There is the notion to address that there are certainly times in daily activity when an individual transitions almost straight from sitting to walking & vice versa. Imagine forgetting that the stove is on while you were sitting watching T.V. These events are characterized by a seamless transition from a passive sitting orientation to a cyclic active region, for example, and do not include the passive standing region. It is also possible that this algorithm does not properly classify a stand as such, and so a *Sitting* and *Walking* schema might be temporally adjacent because of this. In these cases, or any case where schema transition, the algorithm considers two things: is there an unclassified (*Other*) region between the unequal schema, and does the transition between the unequal schema make physical sense? In either case, the interim region is interpolated to smoothly and naturally transition from one schema to the next. Obviously, running from the couch to the stove requires some aspect of standing, and the algorithm incorporates this with at least one

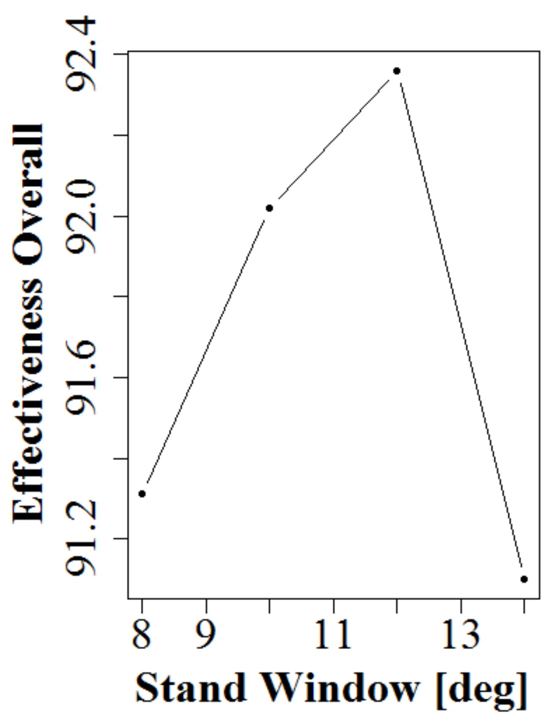

Figure 5.4 Plot of Stand window angle optimization. Presented are half-window values.

instance of *Standing* between a sit and a walk. All unnatural schema transitions are attempted to be resolved in this way.

5.2 Interpretation Of Other Results

Beyond the knowledge of user activity through time, insight can be gleaned on user preferences, lifestyle, and prosthesis effectiveness from secondary algorithm results. These are here discussed with possible interpretation techniques that are appropriate for research and clinical development.

5.2.1 Passive Prosthesis Orientation Array

In categorizing subject behavior data, static regions provide insight into the preferences with which subjects orient their lower leg. The *Standing, Sitting, Lying,* and *Inverted* schema available in this class are comprised of regions of data resulting from the posture of the subject, usually the most comfortable posture for the given behavior. These stretches of time, deemed passive prosthesis orientation arrays, provide to clinicians the angles at which their patients orient themselves and to researchers posture and gait data. Since the algorithm further characterizes these passive regions into schema, subject standing preferences can then be gleaned, for example.

From the orientation arrays the relationship between sagittal and coronal orientation can be investigated. Figure 5.5 presents this relationship in a density plot of passive coronal angle [deg] vs. passive sagittal angle [deg]. The occurrence density is highlighted; ranging from dark grey (zero occurrences), to light and through to the darkest regions (high occurrence). Black dots are presented representing outliers. This presents a depiction of leg orientation in two planes and can be thought of as a top-down (axial) view of leg angle: where the leg is longitudinal and transverse to the body. Typical subject data presents in a rough arc with the apex situated at (0°, 0°), or zero abduction/adduction and zero flexion/extension. The arc is a result of passive stances withdrawing away from 0° longitudinally, where subjects orient themselves over the leg, and opening out from 0° transversely, where subjects orient with near symmetric abduction and adduction of the leg. Such a visual representation of this relationship presents the frequency the subject occupies a certain orientation, the symmetries in the relationship, and offers insight into the effects of the prosthesis build and balance, all valuable aspects in their treatment.

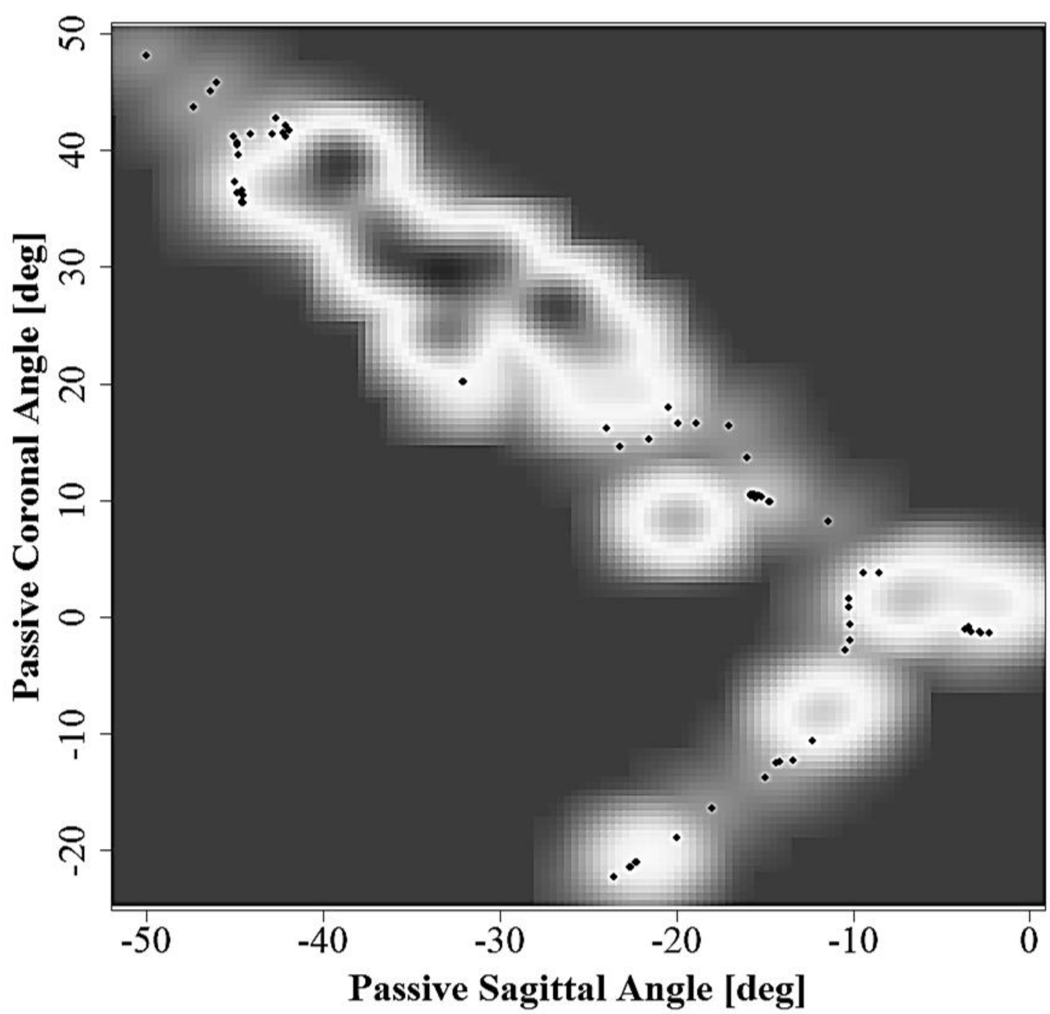

Figure 5.5 Passive orientation relationship density plot. Dark outer regions represent zero occurrences, while grey, white, to black represent transitions to high occurrence regions. Dots represent low occurrence outliers. The plot demonstrates the arc in which human passive stance occupies; a high density at 30° coronal and -30° sagittal.

Various other uses are available regarding the use of passive prosthesis orientation. For instance, the individual array distributions can be examined for symmetry (or does one passive region present oddly), the amount of time being passive can be assessed over a collection period (such as time *Lying*), the global density distribution of passive orientation can be examined for subject preferences (indicated by high occurrence spikes, as in Figure 5.3), or how being active effects a subject's staticity. I let researchers and clinicians invent any other useful presentations and relationships.

5.2.2 Transition Matrix

The interplay between subject behaviors is here interpreted, focusing on the occurrence of behavior transitions. The overall "lifestyle" of a subject can attempted to be described from this interplay, with the treatment – fit, build, components – of the prosthesis affected by subject lifestyle. To

To \ From	Other	Doffed	Inverted	Lying	Sitting	Standing	Walking	Running	Fast	Fall
Fall	0	0	0	0	0	0	0	0	0	0
Fast	0	0	0	0	0	0	0	0	0	0
Running	0	0	0	0	0	0	1	2.9	0	0
Walking	0	0	1	0	0	17	35.9	1	0	0
Standing	0	0	5	0	16	26.2	17	0	0	0
Sitting	0	0	1	1	32.8	15	0	0	0	0
Lying	0	0	1	0	0	0	0	0	0	0
Inverted	1	0	2.2	0	1	5	1	0	0	0
Doffed	0	0	0	0	0	0	0	0	0	0
Other	0	0	1	0	0	0	0	0	0	0

Figure 5.6 Schema Transition Matrix. The plot presents transitions from one schema (top) to the next sequential schema (left side). The transition occurrence counts are in the off-diagonals and the net duration (percentage) spent in the corresponding schema is noted on the diagonal.

capture this, the algorithm constructs a transition matrix which presents the count of transitions from one schema to another linearly in time through the behavior time series.

This matrix is presented for an example subject in Figure 5.6. The matrix is populated with the count of transitions from one schema (top) to another (left side), while the diagonal presents the overall percentage of the trial spent in the corresponding schema. Outside of the diagonal, a color is mapped to the matrix to highlight areas of high schema transition, depicting which schema are transitioned between most often. Schema are arranged such that the off-diagonal should be the most natural transition (i.e. sit-to-lying, walk-to-stand, etc.), while the off-off-diagonal and beyond represent unnatural transitions (i.e. inverted-to-standing).

Such a presentation to researchers and clinicians provides information on user activity and behavior. For instance, low counts of transitions is suggestive of a more sedentary lifestyle, while high counts suggests more activity. While the transition matrix cannot differentiate between lifestyles of constant activity versus intermittent bursts, the percentage spent in each schema might hint at this, allowing treatments to adjust to more active individuals and researchers to identify those who are less mobile, possibly because of an ill-fitting socket or ill-performing prosthesis build.

5.2.3 Cyclicity Metrics

The identification of cyclic regions in subject data sessions offers information on ambulatory behavior and gait. These motions are highly contributive to tissue breakdown and general discomfort for prosthesis users, warranting research and improvements to build, suspension, and other socket technologies. By identifying gait frequency via FFT, it is possible to log cyclic episodes for their frequency, duration, which schema estimate they follow, etc. These metrics could illuminate that cyclic frequency does not decrease in a day with the appropriate liner use or that walk episodes occur less often after periods of long stands. Such insights can be used to better suit treatment to the prosthesis user.

5.3 How Good is Good Enough

The threshold indicating a successful (or acceptable) level of validation within a behavior classification algorithm is an important value to decide on. Consider the various locations where effectiveness is graded: overall effectiveness, class identification effectiveness, and schema identification effectiveness. The vast majority of behavior classifiers and, indeed, classifiers of most types, have decidedly reported and placed most emphasis on the measure of total effectiveness. Should it be the average value reported by related classifiers which is the benchmark for effectiveness, or should the usage of the classifier dictate the desired level of success?

As in most lower limb amputee studies, an overall behavior classification effectiveness greater than 90% was observed here. Such a benchmark – for every ten distinct behaviors, nine were properly estimated – sets a precedent which should be heavily considered. For example, this classifier initially aims to contribute activity information for clinical a research assessment, but ultimately to a socket volume controller. In the first application, specific behavior trends, prosthesis build effects, and gross subject usage is primary over the behavioral nuances which would be paramount to the active controller. Here, the importance of the classification usage and how it dictates the threshold for success is elaborated on. For instance, if the algorithm were to misclassify an activity, e.g. standing for sitting, the prosthetist or researcher reading the session report would still read the activity as passive and the consequences would be minimal. Within a real-time controller, mistaking standing for sitting has potentially much higher consequences. It might be that an overall efficiency of 99.9% is a necessary confidence in a real-time activity monitor, whereas 92.02% is overkill for usage within a post-collection assessment setting.

This aspect of ultimate usage and the significance it has in setting classification expectations is devoid in current behavior classification research. It is the opinion here that the overall success grade observed for the optimized algorithm results, again 92.36%, is acceptable for use in post-collection analysis. Development into an on-board real-time activity monitor using the features described here and subject optimization (described in next chapter) will require an increased classification accuracy, especially sit/stand differentiation, as consequences of functional inaccuracy are dire: increasing socket volume at an incorrect time when it must decrease can cause not only residuum pistoning and bell-clapping (the acts of residuum slipping axially or levering back and forth within the suspension), but can lead to a misstep or unintentional doffing.

Algorithm usage should inform developers on the acceptable algorithm success threshold. The question "*How good is good enough?*" must be approached with respect to the eventual beneficiaries of the classification algorithm and the consequences they may face, a keen understanding of the limitations of the system, and the expectations brought to the scientific community. The thesis work here is presented with these in mind, and appropriately applied. With respect to precedents and consequences, any developments towards high-consequence applications are to be complimented by increasing algorithm effectiveness; a value to be set accordingly.

CHAPTER 6: FUTURE WORK AND CONCLUDING THOUGHTS

I will differentiate the possible extensions of this thesis into sections, some pertaining to the issues presented above that have solutions agreeable to the premise of this work and some that don't. Those are now discussed with improvements and afterthoughts also outlined.

6.1 Improvements to Sit/Stand Differentiation

The results presented above indicate that improvements must be made regarding the main factor in the algorithm's categorization accuracy; the differentiation of a sitting and standing subject.

Leg orientation transitions have been investigated in lab behavior studies [37] [40] but few free-living trials have been undertaken. The sit-to-stand and stand-to-sit transition is typically characterized by a slight shift in sagittal leg angle over one to a few seconds [51]. While strict lab behavior has produced encouraging results, daily transition identification will be a complicated characterization, compounded by myriad factors such as thigh and leg lengths, seated height, chair type, etc. While amputee subject transition identification was fruitlessly explored in this study, I believe it warrants continued efforts towards bolstering sit and stand differentiation.

As stated above, other studies have utilized methods such as ML transition feature recognition or strict orientation transition cues to improve passive behavior categorization. These approaches do not align with the goals of a minimal processing scheme for on-board real-time long-term activity categorization as they do not limit power consumption, processing complexity, or permit free-living behavior (or are rather bad at categorizing it). A ML scheme is not appropriate for on-board processing as memory must be allocated for comparison data (feature vectors). Adding accelerometers on more body segments (i.e. thigh) increases instrumentation and evolves away from a simple enclosed system. A more complex RB scheme including more data features, classes, or branches expands computation and also distances the algorithm from simplicity and efficiency. It is not in this way which algorithm accuracy will be improved.

Sensor fusion has been a buzz word since the rise of powerful handheld devices like our tablets and smartphones. Typically discussed in reference to app development, sensor fusion involves the synergy of multiple on-board sensor units to achieve a task which was previously impossible or less accurate. Working to increase accuracy, sensor fusion provides a pathway to increase computational accuracy while still limiting instrumentation and processing complexity.

Applied in this algorithm, the differentiation between *Sitting* and *Standing* schema would be trivial given sensitivity to a feature which varies between these two activities. As an example, a metric sensitive to pressure would vary as a subject stood or sat while their socket were donned, and this could be incorporated into the algorithm as a data feature. Passive regions could be assessed for passive prosthesis orientation as well as this feature, bolstering the characterization power and increasing accuracy. Such a sensor could be intrinsic to the socket wall or part of the accelerometer unit, remaining unobtrusive and minimal.

In a previous investigation of mine, such a sensor was instrumented into a socket to examine waveforms generated from the intrinsic residuum-socket interface. An array of Force Sensitive Resistors (“FSRs”) were embedded into socket walls so as to capture the forces exerted by the residuum onto the rigid socket. While the literal force values were of little use here, the overall trend of the series demonstrated significant variance between activities. While the preliminary results of this investigation are promising, FSRs are known to be power hungry and are ultimately not feasible in long-term and efficient activity monitoring, though as a proof of concept, such a sensor or related metric could be engineered to further improve sit/stand differentiation.

6.2 Evolving to On-board Real-time Processing

Further development can be made into an inline (real-time) processing algorithm. Such a real-time measurement and processing system can be incorporated into quality of life improvement trials, employing feedback to some capacity (i.e. end-of-day results and statistics) or a diagnosis on a new prosthesis build or suspension. Real-time data capture/processing systems, though more computationally and power consumptive, offer prosthesis users insight into how to improve the effectiveness of their prosthesis. Possible extensions of an inline AM feedback system include user announcements to adjust prosthesis fit or fitness activity and step-counting tracking.

An alternate approach is to collect data and offload to a nearby processor for viewing at intervals within a day. An accelerometer device with Bluetooth or USB port connectivity can be designed to handshake with a portable device (i.e. smartphone) and upload data for processing and viewing on the device, much like current fitness trackers. Constant data capture would occur until a synched device relieves the AM of its on-board memory, processes it, and leaves it ready for interpretation while the AM continues to collect.

6.3 Schema Improvements

Data collected from subjects contains infinite categorization potential. Behaviors like “leaning”, “stair climbing”, or even “cycling” are a few possible behavior categories from an unending list that are absent in this (and most) activity classifiers. It is important that AM systems be able to capture data and classify useful behavior, but defining where the line between valuable and extraneous is difficult. Usually, the line is drawn at what is easy and “enough”. The schema and categorization rules here are simply designed to push a little bit past conventional activity monitoring.

Fall detection is an important tool within health care and certainly a relevant and useful component of this algorithm. With extensions to ageing [52], amputee care [53], and in general, identifying and logging such an event is critical to understanding and optimizing the safe treatment for the individual. The fall detection system here is derived from work done by Mathie and is described in [38]. While I believe this work to be adequate, improvements might be made in its calculation efficiency and eventual extension to an on-board real-time system, outlined here [54].

Walking speeds are of interest to amputee gait researchers. The methods used here to differentiate the two cyclicity states are intuitive, though expansions can be made to include either more walking categories or to include other cyclic behaviors. One such behavior that is of known importance to researchers is stair climbing. Stair climbing is known to be a source of high activity and danger for aged, diseased, and debilitated [55], and is a recognized challenge to amputees. Proper identification of these events in a subject’s life can offer insight into how and with what fitness stairs are negotiated and how best to engineer a prosthesis to accommodate stairs.

The categorization of data regions based on the Active 1 and Active 2 pathways might lend itself to a similar categorization criterion for the Passive class. The interim regions – where passive and active criteria are not met – can fall into the transition class. Currently, passive regions are all of those which are not classified as active, while transition regions are imposed upon the time series afterwards (see Figure 3.4). It is conceivable that the same criteria for the active pathways – a value and duration threshold – be imposed to seek passive regions by negating the value criteria used by the active class. From some general experimentation I know this to produce nearly equal region differentiation, but the variation deserves more investigation. For instance, the regions of Active 1 and (nearly) equal and opposite Passive 1 regions seem to overlap the slightest. This overlap can be found through “and-ing” the arrays and appears to align well with the current Transition class regions. This could also just be another route to arrive at nearly the same processing goal. There are more than one ways to code a cat, they say.

6.4 Subject Optimization

There are a few parameters in this algorithm which could be evaluated in future accessory experiments. The characterization parameters such as passive schema estimation thresholds for standing or the walk/run frequency threshold might be influenced by subject age, gender, or some other factor. The anthropomorphic attributes of subjects is already suggestive of algorithm exclusion criteria or of optimization based on subject anatomy, see Figure 5.1. The effects of these factors ought to be assessed with the benefits of tailoring the processing results to the individual and increasing categorization accuracy.

The utility of *a priori* knowledge within the algorithm architecture is of future interest. For this usage, a probability of schema estimates must be generated for a particular region, where the estimates are weighted based on current region features and some factor based on prior knowledge. The *a priori* data can manifest itself within pattern matching, where past schema successions influence present succession estimates, or in the overall activity distribution of the subject based on transition matrix information. The usage would tailor activity classification to the individual subject as it could be their own prior activity used in the generation of schema probabilities. While this shifts the RB scheme towards ML applications, the ultimate algorithm would be better suited for accurate behavior classification, which is the desired output. The usage of prior subject data must be responsibly used though: memory allocation must be considered as well as the influence it has in weighting a prediction. For example, if a subject typically progresses from *Sitting* to *Standing* to *Walking*, the algorithm should not override the actual possibility of Sitting to Standing to *Sitting*.

6.4 Other Algorithm Studies

Beyond parameter evaluations, some other studies might include the validation of the ActiGraph AM with a secondary accelerometer, a comparative study of subject "activity level" with their peers using this accelerometer and algorithm, or evaluating gait adjustments after a prosthesis is re-built or altered. These and other experiments will invaluably contribute to the development of this algorithm and the lower limb amputee community.

6.5 Concluding Thoughts

From these improvements an AM system could be developed that is more robust to daily activity monitoring and behavior categorization. It can employ an efficient system of sensors sensitive to power constraints, capable of inline processing and real-time user feedback versus post-processing analysis at a clinic appointment.

From the current position and proposed extensions of this thesis, a healthy future for lower limb prosthesis treatments is projected. With user comfort at the forefront - aiming to benefit amputee standard of living - a device like this will yield profound insights into where prosthesis treatments can improve their user's quality of life both initially; after a lifestyle-tailored prosthesis can be built, and dynamically over the lifetime of the device as their lifestyle – and prosthesis – changes.

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