An Inertial Measurement-Based Gait Detection System for Active Leg Prostheses

by

Benjamin Baruch Aisen

Sc.B., Brown University (2005)

Submitted to the Program in Media Arts and Sciences
in partial fulfillment of the requirements for the degree of

Master of Science

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2007

Author ....
Program in Media Arts and Sciences
August 20, 2007

Certified by ....
Hugh Herr
Associate Professor, Media Arts and Sciences
Thesis Supervisor

Accepted by ....
Prof. Deb Roy
Chairperson, Departmental Committee on Graduate Studies

An Inertial Measurement-Based Gait Detection System for Active Leg Prostheses

by

Benjamin Baruch Aisen

Submitted to the Program in Media Arts and Sciences
on August 20, 2007, in partial fulfillment of the
requirements for the degree of
Master of Science

Abstract

Active leg prostheses can lead to more natural and less energy consuming gait patterns for amputees than passive prostheses can, because they provide a better approximation of the functions of the human leg. Active prostheses use motors to supply torques for added force and greater control at the joints (replacing the functions of normal limb musculature). The necessary amount of torque to apply must be closely correlated with gait characteristics. To properly control an active prosthesis, it is necessary to determine whether one is walking at a stable or varying velocity, on level ground, stairs, or a hill or ramp, and in the latter cases whether one is ascending or descending. In all cases, it is essential to detect transitions between gaits as early as possible, ideally before the foot makes contact with the ground, in order for the control system to adjust accordingly. In this thesis, a sensor system for a lower leg prosthesis is described, and a method for determining the gait transitions from this system are presented. The sensor system consists of an inertial measurement unit comprising three accelerometers and three rate gyroscopes installed on the prosthetic limb and a set of strain gauges on the limb to detect changes in force. Using this instrumented prosthesis, data are collected while an amputee participant transitions from level ground to stair ascent/descent. These data are then processed using an intent recognition method based on a hybrid discrete-continuous physical model of human walking. This method is evaluated for accuracy and robustness for real-time use.

Thesis Supervisor: Hugh Herr
Title: Associate Professor, Media Arts and Sciences

An Inertial Measurement-Based Gait Detection System for Active Leg Prostheses

by

Benjamin Baruch Aisen

Submitted to the Program in Media Arts and Sciences
in partial fulfillment of the requirements for the degree of

Master of Science

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2007

Thesis Committee

Thesis Reader . . . .
Joseph Paradiso, Ph.D.
Associate Professor of Media Arts and Sciences

Thesis Reader . . . .
Hermano Igo Krebs, Ph.D.
Principal Research Scientist and Lecturer
Department of Mechanical Engineering

Acknowledgments

I would like to thank the entire Biomechatronics group, and especially Hugh Herr, Andreas Hofmann, and Goutam Reddy, for their invaluable assistance with this project. I would also like to thank my parents for their continuing support in these endeavors.

Contents

List of Figures

Chapter 1

Introduction and Rationale

1.1 Active leg prostheses

The traditional leg prosthesis is passive in nature: it acts as a conduit for the energy applied to it by the amputee's body, but does not provide any additional force of its own. The muscles in a healthy natural limb can apply a nonconservative motive force at the ankles to help power the body forward; this is not possible for a conventional prosthesis. As a result, the motion of such a prosthesis is awkward in nature and can require significant additional energy expenditure on the wearer's part. [4, 7] Though the use of passive springs on the ankle to store and release energy on each step can reduce expenditure somewhat [11], a potentially more effective method is the use of an actuator to apply a torque at the ankle and/or knee. Only recently have advances in engineering and embedded systems made such an active prosthesis feasible for production. Two active knee prostheses, the Rheo Knee and C-leg, have proved more metabolically efficient than an equivalent passive prosthesis [8], suggesting that an active ankle prosthesis could be similarly effective.

One problem in the development of an active prosthesis is determination of a control policy: what quantity of torque to apply at each motorized degree of freedom at each time. The function of the ankle varies significantly with the type of terrain: there is substantially greater energy absorption in stair descent than in level-ground walking, and conversely, greater energy expenditure in stair ascent than in either descent or level-ground walking [5]. As such, it becomes necessary to provide current data on the amputee's gait to the active prosthetic control system. Thus, a portable gait analysis system must be developed to supply this needed data to the motor control system.

1.2 Gait data collection methods

A common method for gait analysis is the use of visual motion-capture data to determine information; this requires specific equipment that can only be practically be applied in a laboratory setting and is infeasible for a portable gait analysis system. The use of electromyography (EMG), the detection of the state of a subject's muscles using electrical signals, to determine the current state of the subject's gait is one possibility for a portable gait analysis system, but there are numerous problems with EMG that make its use impractical. The equipment required for EMG is complex and uncomfortable, involving time-consuming preparation every time an EMG-equipped prosthesis is put on or taken off, and the signal-to-noise ratio of EMG data is relatively low.

Inertial measurement units (e.g., gyroscopes and accelerometers), by contrast, are known to detect motion efficiently, a necessity in a small embedded system with low bandwidth availability. A prosthesis-mounted IMU is also much less physically obtrusive than an electromyographic recorder. Systems of inertial sensors have been used effectively in general gait analysis [9, 10, 1, 13], and an accurate method for determining gait from IMUs alone would be less expensive than one requiring both IMUs and EMG data.

1.3 Methods for analysis of gait data

The main focus of this thesis is detection of gait transitions. Specifically, the aim of the work described herein is to determine when the prosthesis wearer is about to start climbing or descending stairs, ideally before the first step hits the ground. There are several potential methods for detecting transitions from the raw output of the motion sensors examined in this thesis; these include a qualitative, rule-based approach to the problem and the use of a hybrid model of detection.

1.3.1 Rule-based analysis

The first method is an attempt to directly draw conclusions about gait types from the kinetic data itself. In simple cases (such as distinguishing standing from sitting), the distinctions are clear and no computationally intensive algorithms are necessary; the orientations of the legs and magnitudes of accelerations can describe such situations easily. The effectiveness of this approach lessens, however, when attempts are made to use it on gait cycles in real time, as the qualitative differences in the motion data for changes in gait modes only become apparent after the first step. Therefore, for an active prosthesis to change its control policy on the first step (as a human leg does), the use of more advanced algorithms becomes necessary. Nevertheless, these rule-based methods may still provide valuable simplifications of the detection process.

The logic methods examined depend on proper calibration of the IMU system, and use both direct outputs (linear acceleration, angular velocity) and results that can be determined from the outputs using basic physics (e.g., linear position and velocity and angular orientation). Force detection, using either the strain gauges or dedicated force sensors, greatly enhances the capability of such rule-based analysis as it provides direct evidence of the exact times of heel-strike and toe-off for each step.

1.3.2 Hybrid estimation

A more advanced method for gait detection is that of hybrid estimation [6], which combines estimation techniques to predict the future trajectories of both continuous and discrete variables. A major method for estimation of continuous variables is the Kalman filter, which works well in eliminating noise and predicting future state along a single trajectory; the hybrid model uses a hidden Markov model to predict which of several discrete state trajectories is to be followed and multiple Kalman filters to track the most probable future continuous state trajectories.

A particular problem to the gait-estimation application of hybrid estimation is development of a physical model within which the hybrid methods may be applied. In particular, an early attempt has been made to use expectation-maximization (EM) to estimate the parameters of a hybrid model [3]. EM for hybrid models is still largely experimental, but has potential to greatly improve the efficacy of hybrid models where the parameters of a system are unknown.

A notable obstacle to the implementation of hybrid estimation in this particular case is the lack of explicit control commands to the prosthetic limb; the direction to be taken must instead be computed from the motion of the limb, and this thesis intends to determine whether such detections can be made well enough to produce an accurate hybrid model of gait.

1.4 Overview of thesis

The remainder of this thesis is structured as follows:

- **Chapter 2** contains further background information on the gait estimation problem and the underlying mathematics of the method of hybrid estimation.
- **Chapter 3** describes the hardware used and the trials conducted.
- **Chapter 4** details both data analysis methods used: the rule-based analysis and the hybrid-estimation-based method.
- **Chapter 5** describes the results of the various data analysis methods and discusses their significance towards future goals in this research.

Chapter 2

Background

Hybrid estimation is built upon the *Hidden Markov Model*, a method for estimation of discrete modes, and the *Kalman filter*, a method for noise reduction and estimation of continuous variables. In this chapter, these basic methods are described and their combination to form a hybrid Markov observer is explained.

2.1 Hidden Markov Models

A *Hidden Markov Model* can be used to model the state of an indirectly observed discrete variable. The HMM consists of the set of possible hidden modes, the set of values of observed variables, the set of probabilities that the system will transition to each mode given the mode at the previous time interval, and the set of probabilities that each observed value will result from a given hidden mode. There are three basic problems in the theory of hidden Markov models: the determination of the likelihood of an observation sequence given the HMM's parameters, the determination of the most likely hidden mode sequence given an observation sequence and the HMM's parameters, and the adjustment of the HMM's parameters to best fit a given observation sequence. [12] For an intent recognition problem such as gait mode determination, the most pertinent of these problems is the second, hidden mode estimation, for which the *Viterbi algorithm* is the standard technique.

In essence, the Viterbi algorithm is a dynamic programming method: it tracks the probabilities of all modes at the previous timestep, from which the mode probabilities of the current timestep can then be derived. As described in [6], there are two phases in the calculation of the believed mode at a given timestep: the intermediate belief state is a probability based on the previous final belief state and the HMM's transition probabilities, and the final belief state is a normalization of the intermediate belief state based on the observed variables and the HMM's observation probabilities. For each hidden mode m_i in the hidden mode set $\mathcal{M}$, the intermediate belief $b_{(\bullet k)}[m_i]$ at time k is as follows:

$$b_{(\bullet k)}[m_i] = \sum_{m_j \in \mathcal{M}} P_{\mathcal{T}}(m_i|m_j) b_{(k-1)}[m_j]$$

and the final belief $b_{(k)}[m_i]$ is:

$$b_{(k)}[m_i] = \frac{b_{(\bullet k)}[m_i] P_{\mathcal{O}}(y_{d,(k)}|m_i)}{\sum_{m_j \in \mathcal{M}} b_{(\bullet k)}[m_j] P_{\mathcal{O}}(y_{d,(k)}|m_j)}$$

where $P_{\mathcal{T}}$ and $P_{\mathcal{O}}$ represent the transition and observation probabilities respectively and $y_{d,(k)}$ is the observed discrete state at time k.

In the full Viterbi algorithm, the most likely trajectory over many timesteps is determined by calculating the belief state for the final timestep in this manner, then backtracking over the most likely previous transitions to the beginning of the time period analyzed. For real-time estimation, this is unnecessary, as only the most current state is of interest, so the backtracking steps are omitted.

2.2 Kalman Filters and the Probabilistic Hybrid Automaton

A *Probabilistic Hybrid Automaton* (PHA) combines an HMM estimating the discrete mode with *Kalman Filters* to estimate the values of continuous variables. The variant of the PHA used in this thesis work is substantially different from the theoretical underpinnings in [6], most notably in the lack of a control input and the resultant elimination of the Kalman filters as redundant on relatively non-noisy observations. The theoretical basis for the PHA is described here; the particular modifications to the model are detailed in chapter 5.

The continuous variables in the PHA are estimated directly using Kalman filters, with each discrete mode having its own associated Kalman filter to track the projected trajectory of the continuous variables given that it is the current mode. Briefly, the Kalman filter estimates the evolution of continuous variables as a function of the previous continuous state, the control input, and Gaussian process noise, given the control input and a noisy observation whose value is a function of the current state and Gaussian observation noise. In the basic Kalman filter, these functions are linear in all inputs; the extended Kalman filter, used in the PHA, uses arbitrary differentiable functions. The output of the Kalman filter is in the form of a mean and covariance for both the estimated state and the measurement residual.

The discrete modes of the PHA are estimated using the *Hybrid Markov Observer* (HMO), whose behavior is defined by similar equations to the basic HMM:

$$h_{(\bullet k)}[\hat{\mathbf{x}}_i] = P_{\mathcal{T}}(\mathbf{m}_i|\hat{\mathbf{x}}_{j,(k-1)})h_{(k-1)}[\hat{\mathbf{x}}_j]$$

$$h_{(k)}[\hat{\mathbf{x}}_i] = \frac{h_{(\bullet k)}[\hat{\mathbf{x}}_i]P_{\mathcal{O}}(\mathbf{y}_{c,(k)}|\hat{\mathbf{x}}_i)}{\sum_j h_{(\bullet k)}[\hat{\mathbf{x}}_j]P_{\mathcal{O}}(\mathbf{y}_{c,(k)}|\hat{\mathbf{x}}_j)}$$

Here $\hat{\mathbf{x}}_j$ is an estimate of both discrete and continuous state based on the Kalman filters associated with mode m_j. The key difference is in the makeup of the transition and observation probability functions: in the basic discrete HMM they are simply parameters of the model, but in the HMO they are functions of the estimated continuous state. The transition function is a multivariate integral of the Gaussian probability of the estimated continuous state over the region where the mode's guard conditions are met; the observation function is the probability of the observed value within the residual Gaussian.

(Note that the input variables $\mathbf{u}$ are present in the original theoretical work; they are absent here because the PHA described is a pure observer and does not provide any input to the system.)

Chapter 3

Experimental Overview

3.1 Hardware

For purposes of the data collection trials, sensors were attached to a standard passive ankle prosthesis. The prosthesis used is an Ossur LP Vari-Flex with an inertial measurement unit affixed to the toe area and strain gauges attached to the metal shank of the leg.

The inertial sensor used is the commercial MicroStrain 3DM-GX1 unit, which includes three angular rate gyroscopes and three orthogonally mounted DC accelerometers. It outputs linear acceleration in three dimensions, angular velocity in three dimensions, and an orientation vector computed from the raw sensor outputs.

The purpose of the strain gauges on the prosthesis is to detect axial compression force, mediolateral torque, and anterior-posterior torque. The strain gauges are used primarily to detect the times of foot-strike and foot-off; since their output values are dependent upon the design of the prosthesis used, conclusions drawn from them may not necessarily be usable on a prosthesis of a different design.

Finally, a hand-held button was constructed specifically for the trial and used by the subject to manually mark gait mode transitions; these markers are used in much the same way as the foot event times derived from the strain gauges.

The sensors interface with a wearable PC/104-based computer for purposes of recording data. A photograph of the hardware system in its entirety is included as

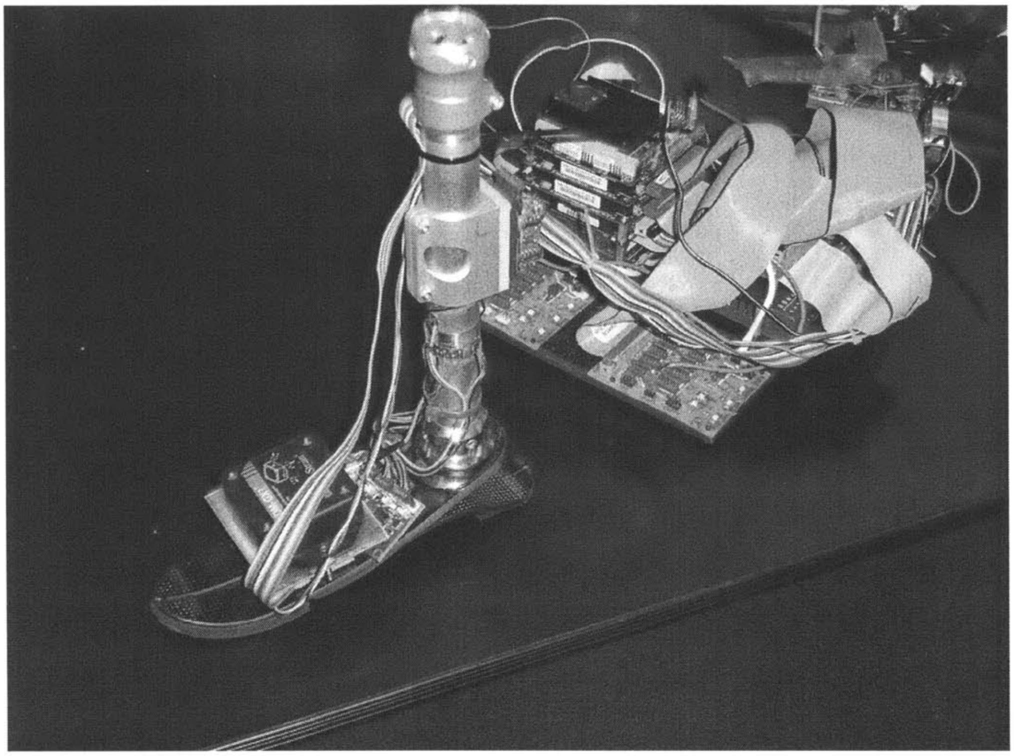

Figure 3-1: The sensor-equipped prosthesis and PC/104 wearable computer used in trials.

figure 3.1.

3.2 Software

Data from the IMU and strain gauges is recorded by the PC/104 running the Matlab kernel. Matlab and Simulink were used extensively in data processing, and the estimation/detection programs described in later chapters were written in Matlab as well.

3.3 Trial description

One trial was carried out in order to collect data of the gait types to be detected. The subject, a healthy male bilateral transtibial amputee (height: 1.8 m, weight: 78 kg, age: 41) wore the sensor prosthesis on his right leg and a conventional non-sensor prosthesis on his left leg.

The experiments were approved by MIT's Committee on the Use of Humans as Experimental Subjects (COUHES). The participant volunteered for the study and was permitted to withdraw from the study at any time and for any reason. Before taking part in the study, the participant read and signed a statement acknowledging informed consent.

3.3.1 Experimental protocol

The subject was recorded standing still, walking on level ground, and repeatedly ascending and descending the staircase in the Media Lab lobby. The subject walked at a steady, self-selected pace throughout the walking portions of the trial. A total of five ascents and five descents were recorded, each of which contains two level-ground-to-stairs and stairs-to-level transitions (at the ends of the staircase and at the landing midway up). The trial also included a long level-ground segment at the start and brief level-ground segments between ascents and descents as the subject turned around. The complete trial lasted approximately five minutes.

Chapter 4

Methods of Data Analysis

4.1 Rule-Based Analysis

4.1.1 Linear acceleration

The initial attempt at rule-based data analysis was to use double integration on the linear acceleration data in the z (vertical) dimension to determine a value for the foot's vertical position relative to its position at the start of the step. From this value, it was hoped, a net upward or downward motion could be detected, thus determining whether the step was ascent, descent, or level motion.

Unfortunately, this apparently straightforward method proved problematic. Simply integrating the raw output of the accelerometer corrected for gravity produced wildly varying results, with net motion of over 10 cm in both directions calculated on all three step types. Even after compensating for potential drift by resetting velocity to zero on each step, the variation in the calculated position was still too great to draw any meaningful conclusions (see figure 4.1.1), and the attempts to use integration of linear acceleration data were reluctantly abandoned.

Further methods of data analysis focused on the angular outputs of the IMU: orientation and angular velocity.

4.1.2 Orientation and angular velocity

The IMU used computes orientation internally by integrating the raw outputs of the angular velocity sensors; the resulting orientation values are relatively accurate, although noticeable drift was present during some portions of the trial.

There were several notable patterns in the angular velocity that differed among level-ground, stair ascent, and stair descent; see figures 4.1.2, 4.1.2, 4.1.2.

These patterns could not be consistently quantified, however, and it was decided that a model-based approach would be of greater use.

4.1.3 Data from strain gauges

The strain gauges clearly delineate periods when the heel and toe are on the ground based on the presence or absence of force on the prosthesis. Precise times of heel-strike, toe-strike, heel-off, and toe-off could be extracted from the strain data, and these were used both to organize the data into discrete steps and in the detection of gait mode itself.

Each of the three gait modes analyzed showed a distinct pattern in the presence and sequence of these gait events. When walking on level ground, there are distinct heel-strike, toe-strike, heel-off, and toe-off events in that order; when walking down stairs, the subject's prosthetic foot struck the ground flat, leading to simultaneous heel-strike and toe-strike events followed by a distinct heel-off and toe-off; and when ascending stairs, the subject's heel almost never touched the ground at all, so only toe-strike and toe-off events were recorded.

The strain gauges provided consistent outputs of zero during the swing phase, so they are of little use in mid-step detection. As the heel and toe events were sufficient for classification among the appropriate states while in stance, the strain values themselves were not used after the extraction of event times.

4.2 Modifications of the Hybrid Estimation Method for Gait Estimation

There are several aspects of the gait estimation problem that required modifications to the basic hybrid estimation method described above. Firstly, in the gait estimation problem there is no control input; the estimator can only passively observe the gait data but cannot affect future gait. The control input variables in the hybrid model can thus be eliminated.

Secondly, the continuous state measurements in hybrid estimation are assumed to be noisy, requiring the use of Kalman filters to estimate the continuous state. In this case, the noise in the orientation and angular velocity measurements was found to be sufficiently low that Kalman filters did not offer significant improvements. So as a simplification to the hybrid model, the Kalman filters were eliminated and instead simple Gaussian models were used to calculate probabilities for the continuous state in each mode.

Finally, as the object of this research is to determine the gait mode before the foot strikes the ground, estimation on each step is stopped after a fixed time (0.5 and 1.0 seconds were used) and the estimated mode reported.

4.2.1 Three-Dimensional Gaussian Modeling

The cyclic nature of the gait data reduces the effectiveness of a simple two-dimensional Gaussian of pitch angle and angular velocity in differentiating gait modes, as the variation within a gait cycle is as great as that between different types of gait cycles. One attempt to alleviate this problem used the time since the last toe-off as the third dimension in a Gaussian model of the data. In this method four segments of each gait cycle (swing, heel on ground, foot flat, toe on ground) were used as separate modes for each of the three gait types, making for a total of twelve modes, each with a three-dimensional Gaussian model. (In fact some of these twelve modes did not occur in the data and were unused.)

See figure 4.2.1 for a block diagram of the three-dimensional modeling method.

4.2.2 Time-Slice Two-Dimensional Gaussian Modeling

An alternative approach retained two-dimensional Gaussian models but split the data points into time slices by elapsed time since last toe-off. Thus a separate two-dimensional Gaussian for each mode was generated for 0.1 seconds since toe-off, 0.2 seconds since toe-off, and so on. Since the foot contact events occurred at consistent times in the gait cycle, the separate modes for gait cycle phases were eliminated for this method and only the three gait type modes were used.

See figure 4.2.2 for a block diagram of the time-slice method. Plots of some of the time-slice Gaussians generated using the entire training set are included as figures 4.2.3-4.2.3.

4.2.3 Parameter estimation

A full expectation-maximization method for estimating the parameters of the hybrid model, as described in [3] was considered. However the presence of mode labels in the training data made much of EM, which determines the parameters and the modes without labels, superfluous. It was therefore decided to use simple maximum-likelihood estimation to determine the parameters of the Gaussians.

In the three-dimensional Gaussian variant, the Gaussian for each gait mode is the mean and covariance of the values of the vector $[\theta\dot{\theta}t]^T$ for each timestep in the training set with the given mode.

In the two-dimensional variant, the Gaussian for each gait mode and each value of t, the elapsed time since toe-off, is the mean and covariance of the values of the vector $[\theta\dot{\theta}]^T$, for each timestep in the training set with the given mode and value of t.

For purposes of this thesis, reasonable manually selected observation and mode transition probabilities were used to inform the hidden Markov model. More systematically determined values for these probabilities would be preferable, but since the training data was abnormal in the high frequency of gait mode transitions, any transition probabilities determined using the training data would be heavily biased.

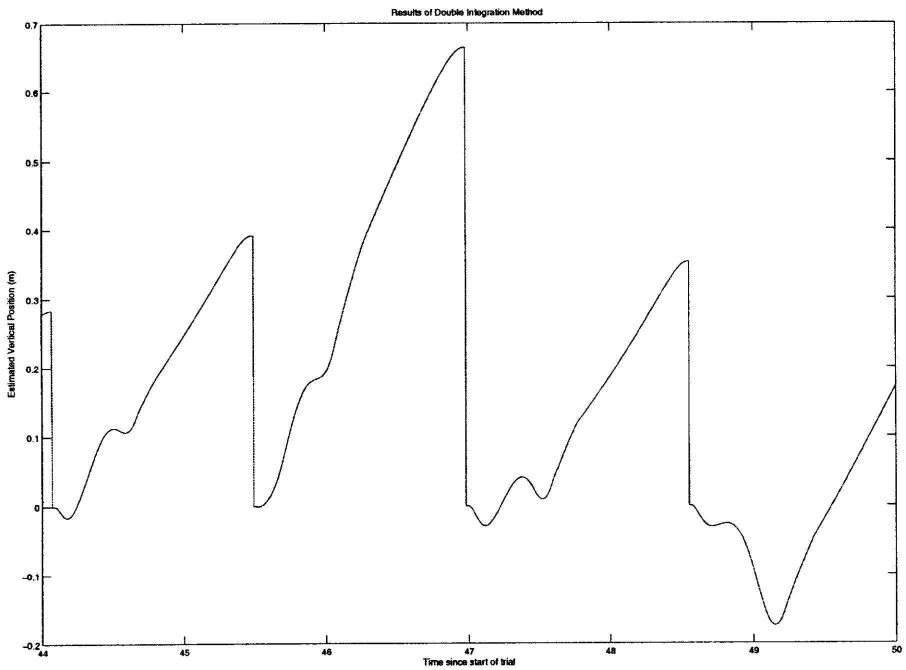

Figure 4-1: Results of double integration

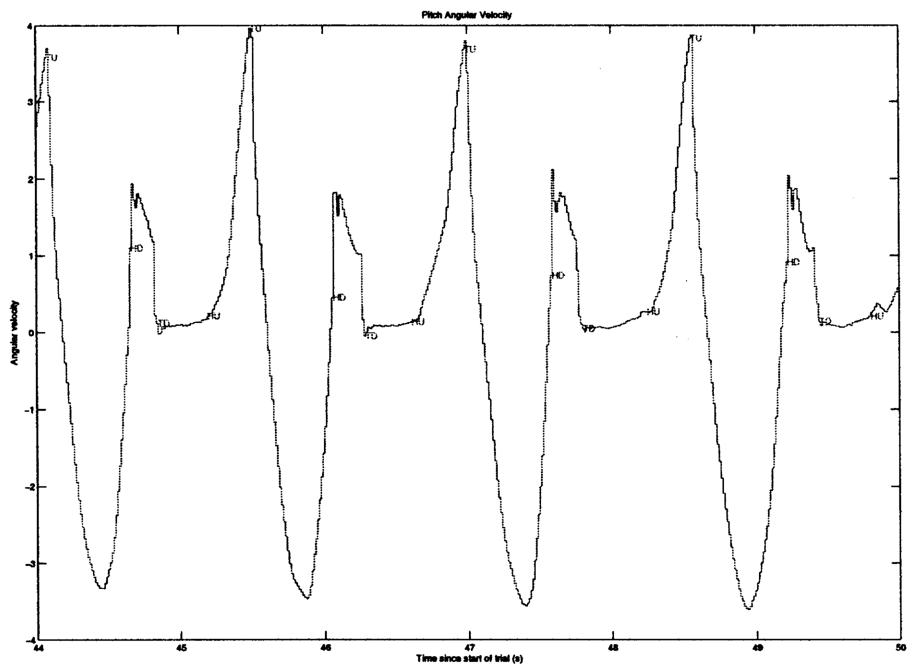

Figure 4-2: Angular velocity patterns - level ground

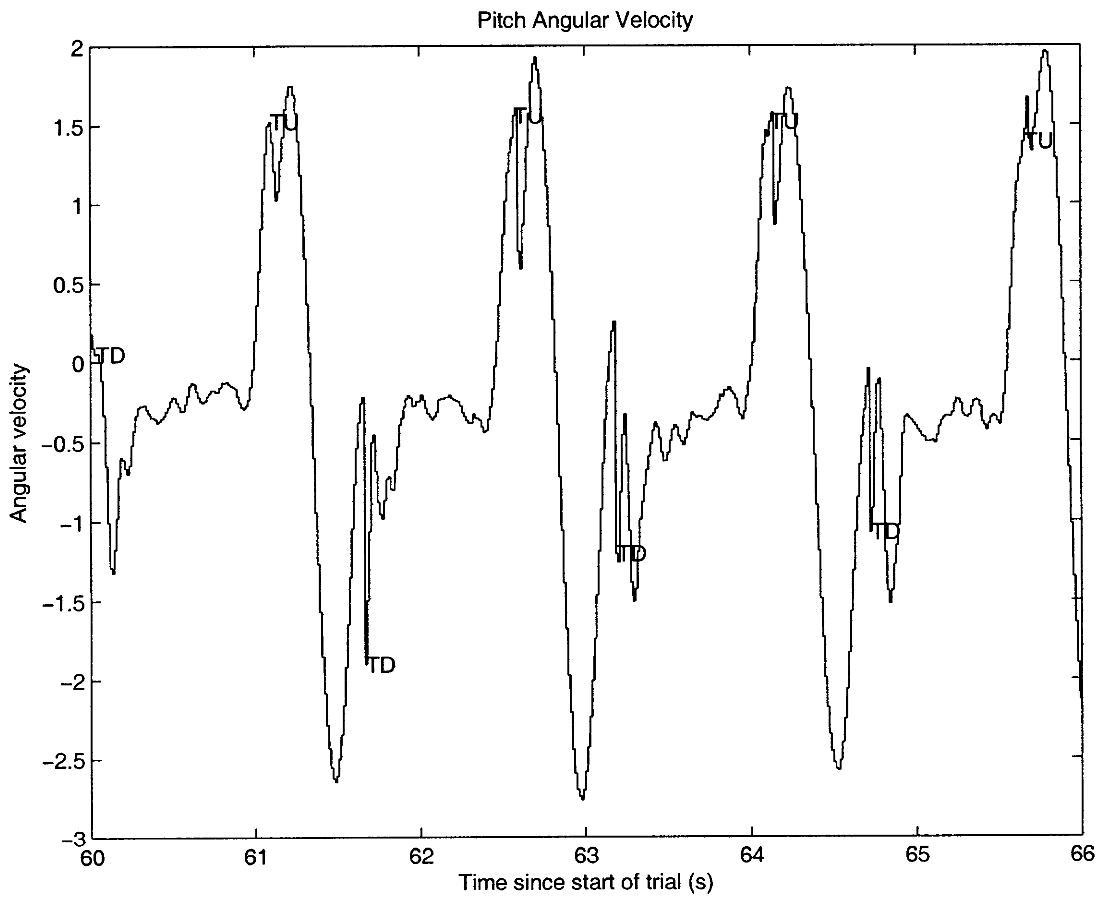

Figure 4-3: Angular velocity patterns - up stairs

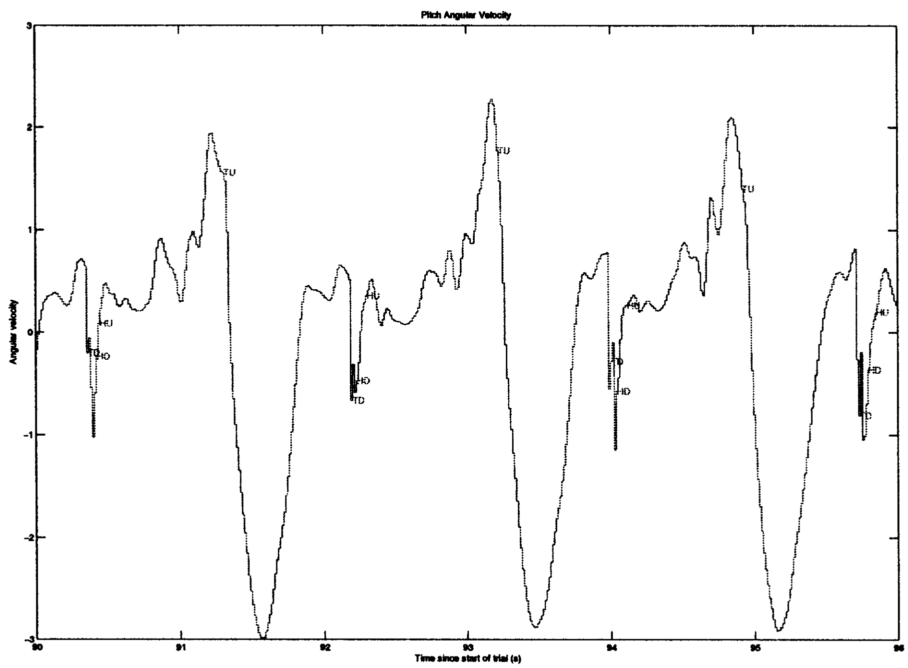

Figure 4-4: Angular velocity patterns - down stairs

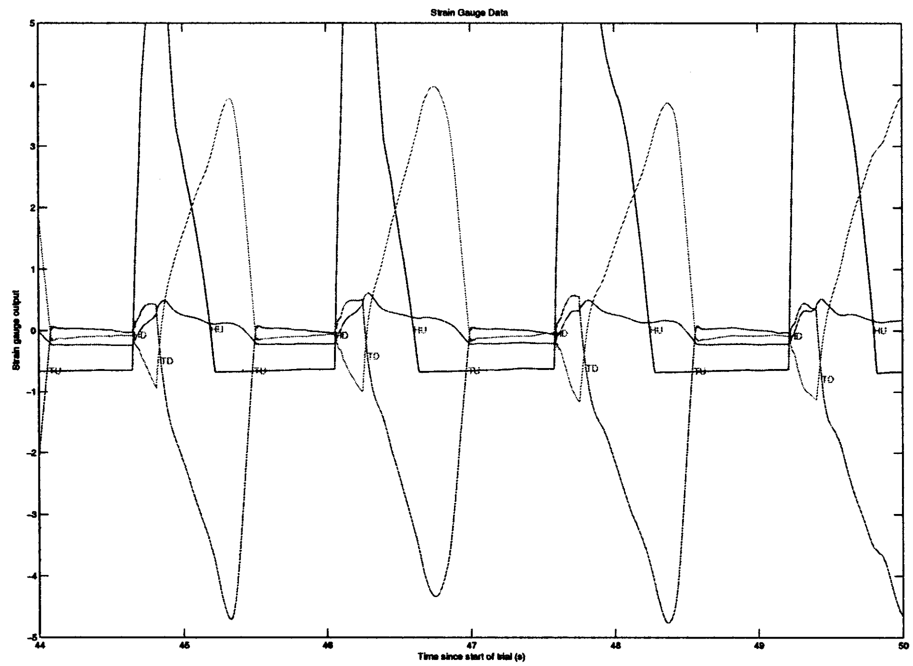

Figure 4-5: Strain gauge data patterns

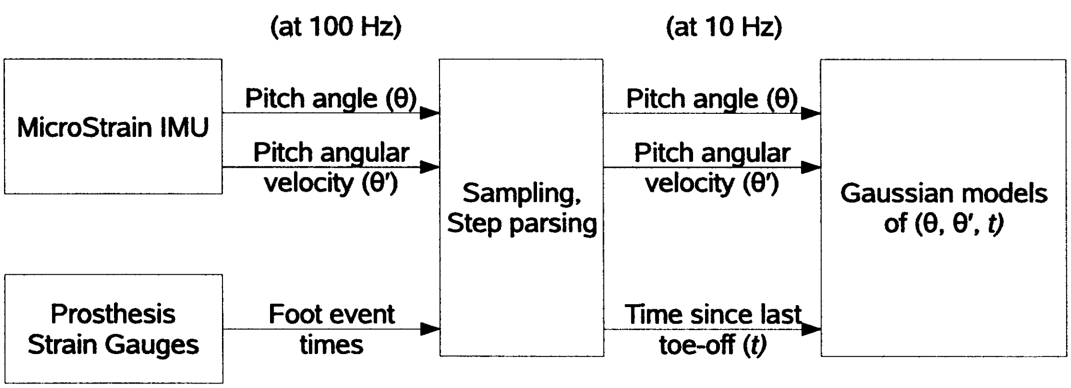

Figure 4-6: Block diagram of three-dimensional modeling method

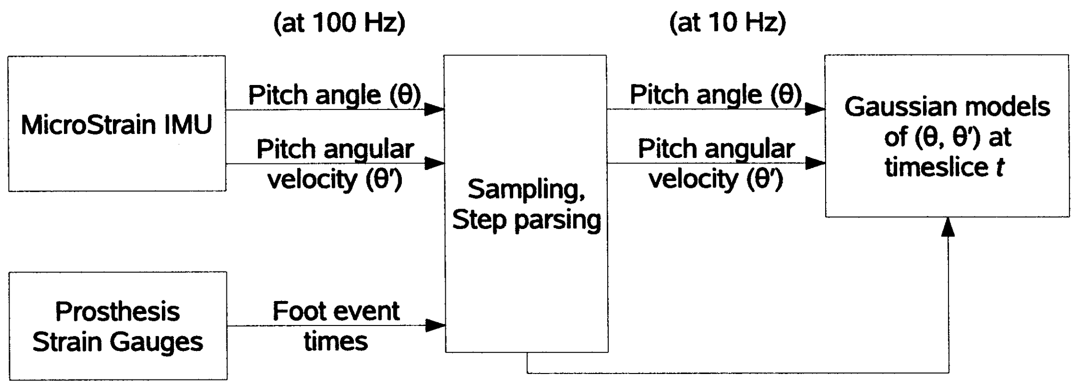

Figure 4-7: Block diagram of time-slice modeling method

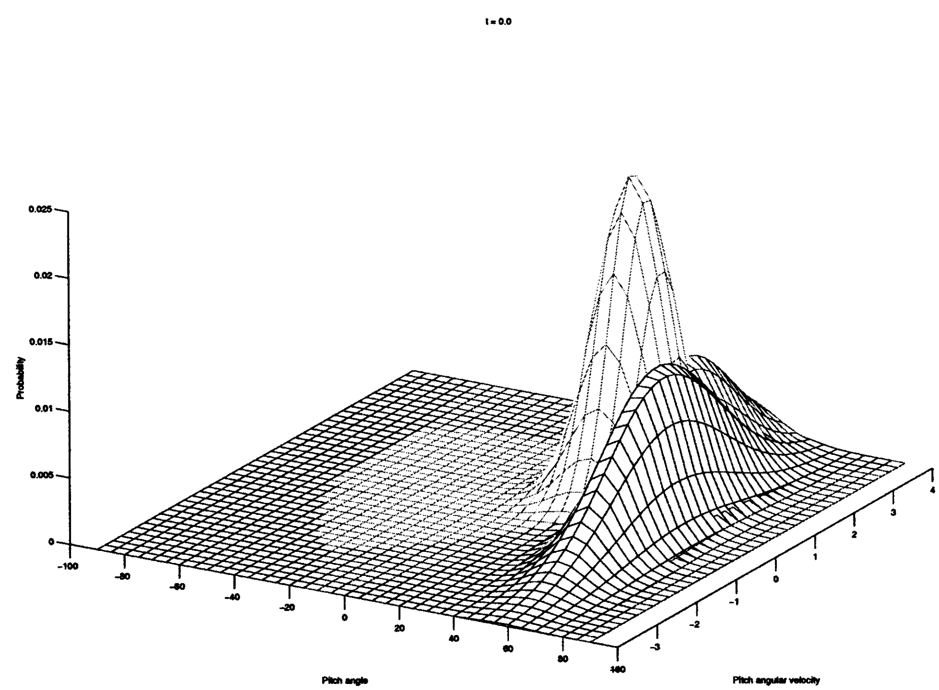

Figure 4-8: Time-slice Gaussian at t=0.0 seconds

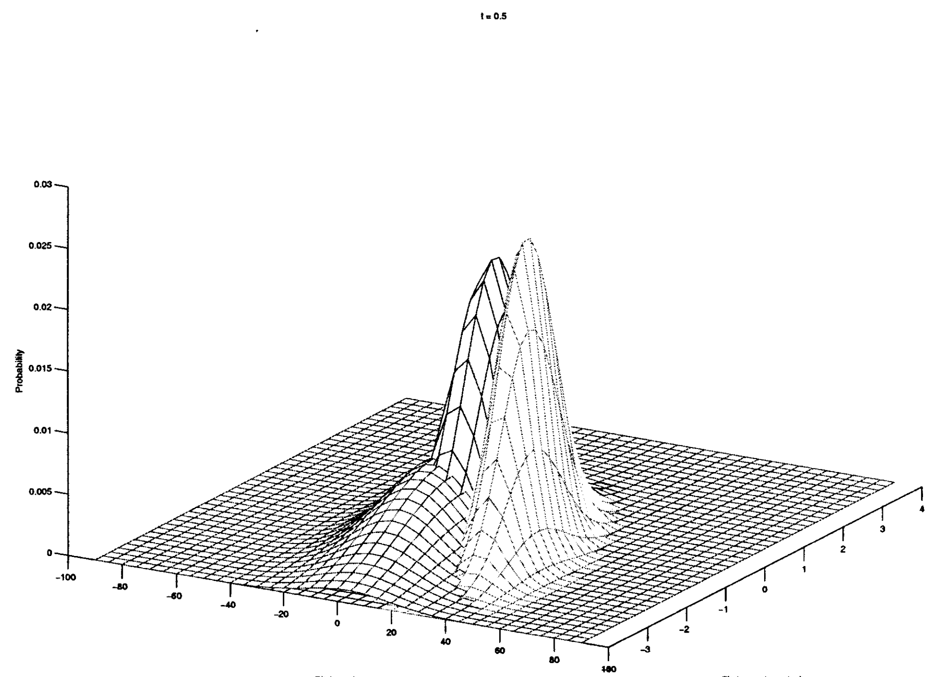

Figure 4-9: Time-slice Gaussian at t=0.5 seconds

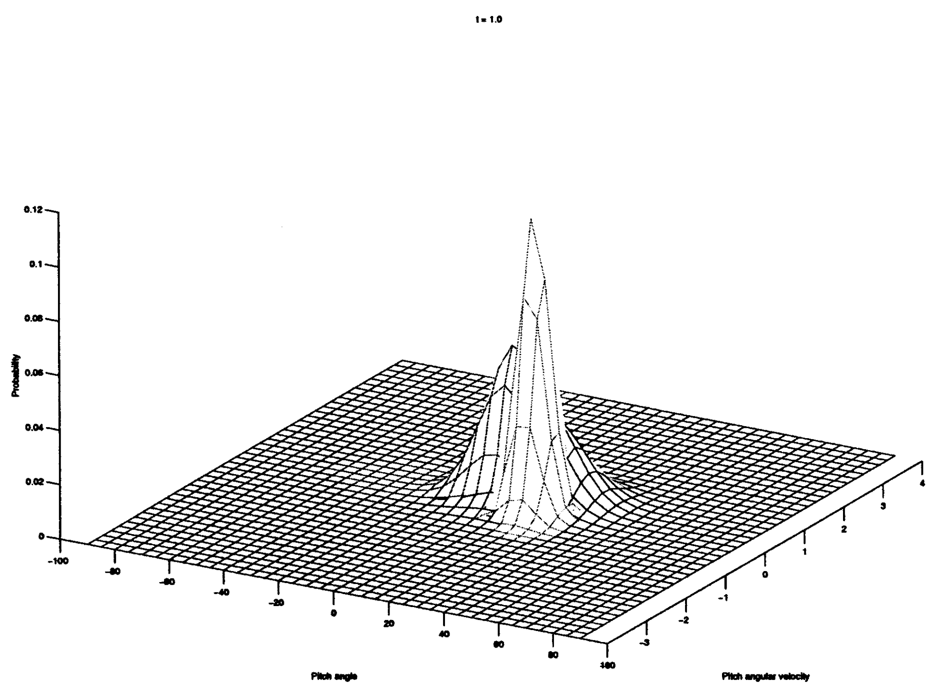

Figure 4-10: Time-slice Gaussian at t=1.0 seconds

Chapter 5

Results and Discussion

5.1 Results

5.1.1 Rule-based method

As discussed in the previous chapter, there was no clear rule-based method for distinguishing the three gait types.

5.1.2 Hybrid estimation

The three-dimensional Gaussian method, in preliminary testing, failed to discern among the gait types; further work on the method was abandoned following the development of the time-slice method, which performed well in initial tests.

The time-slice method was then tested more thoroughly on the data set using tenfold cross-correlation; the success rate was 72%, with 157 of the 218 steps correctly identified within 0.5 seconds. Neither extending the window to 1 second nor changing the number of testing sets for cross-correlation changed this result.

The confusion matrix is as follows:

	Level	Ascent	Descent
Level	73	14	11
Ascent	7	52	3
Descent	26	0	32

Interestingly, most of the failures seemed to occur in the first and last stair descent periods, which were largely misidentified as level-ground walking. The other descents, as well as all the ascents and level-ground periods, were more consistently identified correctly.

5.2 Discussion

Although the time-slice Gaussian detection method was successful in a majority of cases, the issues with the first and last descents raise concerns about its reliability. The reason for the discrepancy in the descent results is as yet unclear; it may be a simple error in the data or involve a gait feature in the middle three descents that is absent from the first and last. A comparison of a descent step incorrectly identified as level-ground (figure 5.2) with a correctly identified descent step (figure 5.2) and a correctly identified level-ground step (figure 5.2) shows that it resembles the level-ground step more closely than the correctly identified descent; the correctly identified descent has a sharp W-shaped curve in the angular velocity towards the beginning of the step, while both the incorrectly identified descent and the level-ground step have a more gradual curve. More extensive testing on multiple subjects will be necessary to determine the true nature of this problem and whether it is possible to overcome it.

Once these issues are resolved, potential next steps include adaptation to real-time operation and integration of the detection system into a control policy. A real-time version of time-slice Gaussian detection should be fairly straightforward to adapt, given that the method does not use any knowledge of future state to predict the present state. Once the real-time conversion is complete, use of the results of this detection method to select an appropriate control policy should also be a straightforward adaptation but may require additional modification to the detection code depending upon the control hardware and software used in the active prosthesis.

Beyond the scope of this thesis are other detection methods considered but not developed. In particular, model-free methods such as the support vector machine [2]

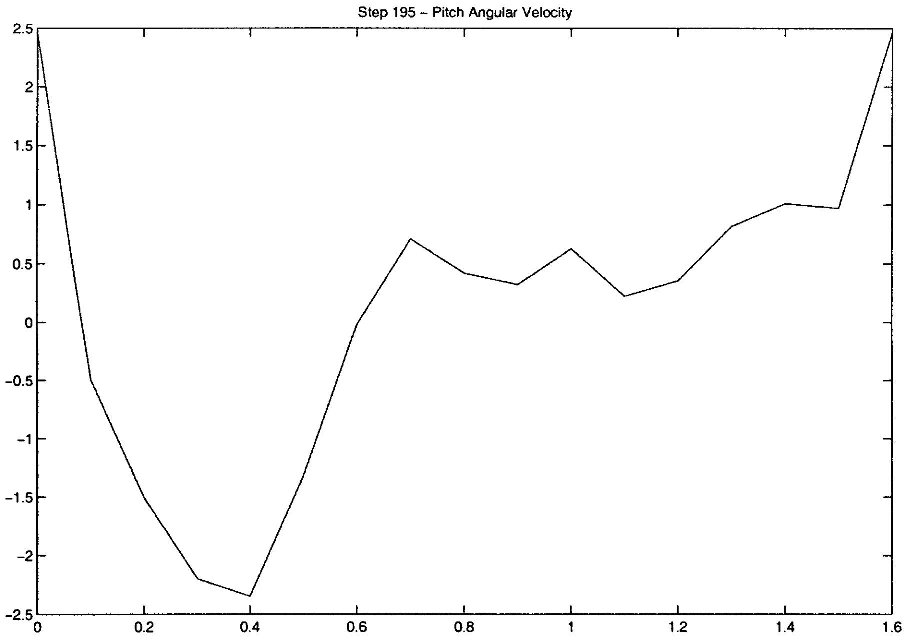

Figure 5-1: Angular velocity of descent step misidentified as level-ground.

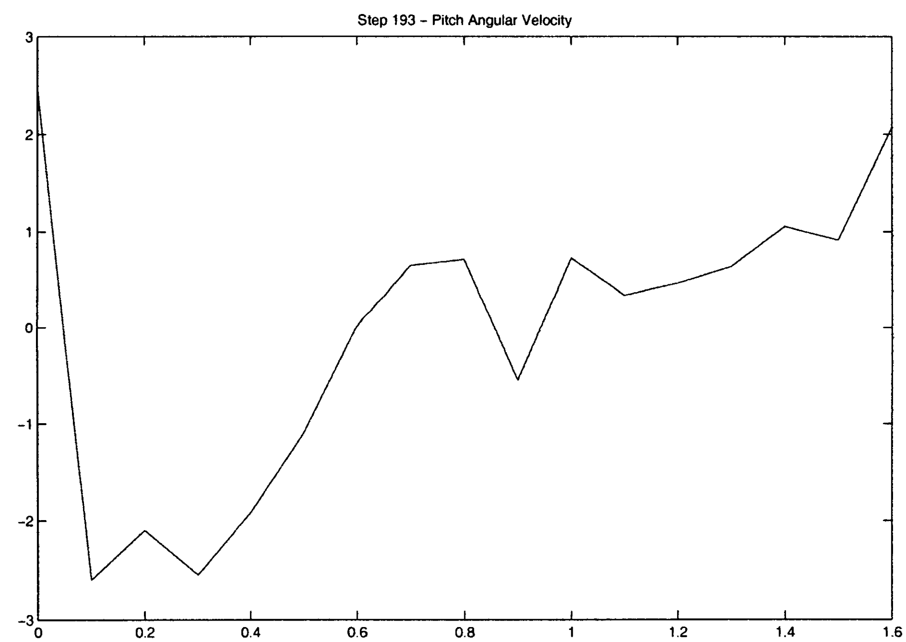

Figure 5-2: Angular velocity of correctly identified descent step.

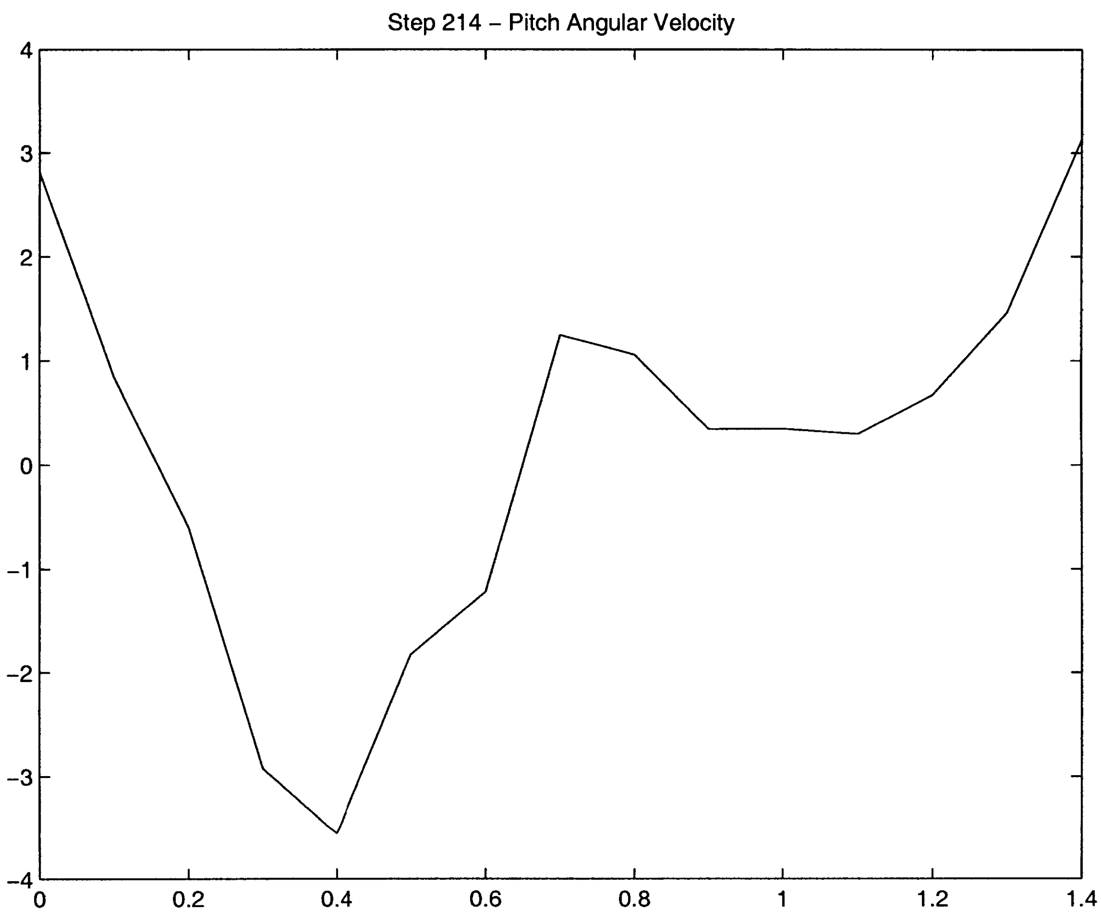

Figure 5-3: Angular velocity of correctly identified level-ground step.

could also provide a basis for a real-time gait detection system, and a comparison of such methods with the hybrid time-slice Gaussian method would be valuable as well. Additional problems for future work include estimating additional gait modes, such as ramp ascent and descent, whose distinguishability from level-ground and stair ascent and descent has yet to be determined.

Despite the minor problems with reliability, the hybrid gait estimation method discussed herein is generally an effective method and has strong potential for use in the next generation of active prostheses.

Bibliography

[1] S J M Bamberg, A Y Benbasat, D M Scarborough, D E Krebs, and J A Paradiso. Gait analysis using a shoe-integrated wireless sensor system. *IEEE Transactions on Information Technology in Biomedicine*, 2007.

[2] Christopher J. C. Burges. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2(2):121–167, 1998.

[3] S H Chung and T Mikaelian. Learning parameters of probabilistic hybrid automata using an expectation-maximization algorithm. Courtesy of the authors, 2005.

[4] S F Crouse, C S Lessard, J Rhodes, and R C Lowe. Oxygen consumption and cardiac response of short-leg and long-leg prosthetic ambulation in a patient with bilateral above-knee amputation: comparisons with able-bodied men. *Arch Phys Med Rehabil*, 71(5):313–317, Apr 1990. Comparative Study.

[5] D Gates. Characterizing ankle function during stair ascent, descent, and level walking for ankle prosthesis and orthosis design. Master's thesis, Boston University, 2004.

[6] M W Hofbaur and B C Williams. Mode estimation of probabilistic hybrid systems. In *Lecture Notes on Computer Sciences*, pages 253–266, 2002. Hybrid Systems: Computation and Control.

[7] D Hunter, E Smith Cole, J M Murray, and T D Murray. Energy expenditure of below-knee amputees during harness-supported treadmill ambulation. *J Orthop Sports Phys Ther*, 21(5):268–276, May 1995. Clinical Trial.

[8] J L Johansson, D M Sherrill, P O Riley, P Bonato, and H Herr. A clinical comparison of variable-damping and mechanically passive prosthetic knee devices. *Am J Phys Med Rehab*, 84(8):563–575.

[9] S J Morris and J A Paradiso. Shoe-integrated sensor system for wireless gait analysis and real-time feedback. In *Proceedings of the Second Joint EMBS/BMES Conference*, pages 2468–2469, 2002.

[10] I. P. I. Pappas, M. R. Popovic, T. Keller, V. Dietz, and M. Morari. A reliable gait phase detection system. *IEEE Trans Neural Syst Rehabil Eng*, 9(2):113–125, 2001.

[11] F Prince, D A Winter, G Sjonnensen, C Powell, and R K Wheeldon. Mechanical efficiency during gait of adults with transtibial amputation: a pilot study comparing the SACH, Seattle, and Golden-Ankle prosthetic feet. *J Rehabil Res Dev*, 35(2):177–185, Jun 1998. Clinical Trial.

[12] L Rabiner. A tutorial on hidden markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2):257–286, February 1989.

[13] K Van Laerhoven and O Cakmakci. What shall we teach our pants? In *ISWC*, pages 77–, 2000.