iBALANCE

Hardware and Software Design for a Mobile Diagnostic Device that Assesses Human Balance

Qian Yang, Bradford Diephuis, Virginia Chu and Katharine E. Forth
iShoe Research Team, Cambridge, U.S.A.

Keywords: Balance, Stabilometry, Diagnostic, Mobile.

Abstract: Balance deterioration is a major risk factor for falling, particularly among the elderly. Early detection of emerging balance problems can allow behavioral and medical interventions to reduce the impact and severity of balance-related incidents. The iBalance technology presents a small, mobile platform that integrates hardware and software engineering for balance monitoring at a low cost for use in the home, physical therapy office, or other point of care setting. The hardware solution has the form factor of a bathroom scale and takes the standard approach of a force plate with four load cells arranged in the corners beneath the platform. The load cells output 12-bit data to a computing device running the accompanying software. There is less scientific consensus about the most effective software solution for performing analysis on balance data. A survey of the literature reveals 16 commonly used metrics of balance derived from force plate data. Using principal component analysis, we identify three underlying clusters of metrics from which a representative metric for each cluster may be chosen to construct an exogenous balance score. Finally, we have developed a graphical user interface for the iBalance that allows researchers to collect raw and/or processed data and view analytic visualizations of the data, with ease of extensibility for further research and analysis.

1 INTRODUCTION

Deterioration of balance is a common and pressing problem for senior citizens. Injury from falls is one of the leading causes of accidental death in adults over 85, and among adults 65 and over a hip fracture is statistically fatal 25% of the time within 6 months of injury. According to the Centers for Disease Control and Prevention, the total direct cost of all fall injuries for people 65 and older in the year 2000 exceeded $19 billion (CDCP, 2009). The high health and financial costs associated with poor balance point to a large unfulfilled need for diagnostic technology that can help prevent fall risk and detect deterioration of balance at an early stage.

Currently, the main method of addressing this problem has been clinical assessment followed by physical therapy. Clinical assessments have been largely limited to qualitative observation over short time spans by a physician. Some commonly used techniques include evaluative questionnaires such as the Berg Balance Scale (Berg et al., 1992), and the observation of quiescent standing on a foam board where somatosensory inputs are impaired (Emery et al., 2005).

Early diagnosis of balance deterioration enables a host of treatment options including medication, tai chi, physical therapy, safety equipment such as walkers, and simple adjustments to the home such as rugs and hand rails. However, a missing link in this process is the long-term monitoring and early diagnosis of balance deterioration. Because the effects of balance deterioration are subtle, it is difficult to assess one's own balance in a timely manner to take preventative measures before a fall occurs. The inconvenience of scheduling regular balance monitoring checkups with a physical therapist in the absence of clear physical symptoms, and the high cost of existing devices such as NeuroCom units (Chaudhry et al., 2004) used in state-of-the-art facilities, make long-term balance monitoring prohibitively inefficient for most individuals.

Yang Q., Diephuis B., Chu V. and E. Forth K..
iBALANCE - Hardware and Software Design for a Mobile Diagnostic Device that Assesses Human Balance.
DOI: 10.5220/0003174001070114
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2011), pages 107-114
ISBN: 978-989-8425-34-8
Copyright © 2011 SCITEPRESS (Science and Technology Publications, Lda.)

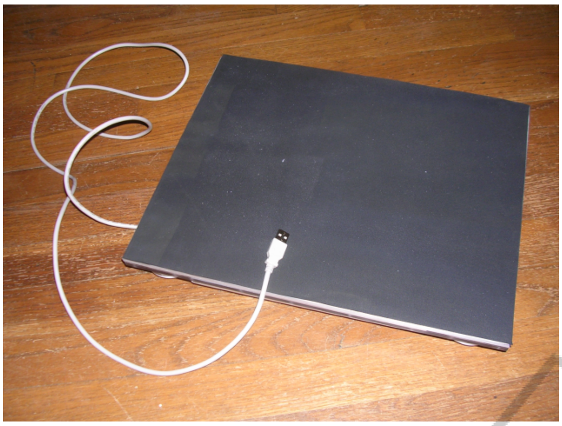

Figure 1: iBalance hardware consisting of a force platform with an USB extension chord for connection with an external computing device. The device has dimensions of 17” x 14” x .25” and weighs less than 10 lbs; substitution of lighter materials for the metal casing can significantly reduce the weight and increase the portability of the device.

2 HARDWARE DESIGN

The iBalance is a cost-effective, portable, user-friendly diagnostic device that can be used from the comfort of the home or at any point of care setting. The device consists of a durable balance platform equipped with pressure sensors and a USB serial port that transfers data collected from the platform onto any USB-enabled computing device. Alternatively, wireless bluetooth may also be used. The data from the balance platform is collected and displayed in real time by the computing device, which then computes a balance diagnostic score based on a fixed interval of data, usually between 20 and 120 seconds. The final prototype of the device will be able to compute a simple diagnostic internally so that an external computing device will not be necessary; this is the adaptation most suitable for home use, while in clinical applications the use of a computing device with the ability to conduct more detailed analysis on the data may be preferable.

2.1 Mechanical Design

The iBalance hardware consists mainly of a set of load cells and a stable platform for the subject to stand on. Since the basis of the iBalance software relies on changes in the center of pressure (COP) in the anterior-posterior and medio-lateral directions, at least three measures of pressure are required to calculate the COP in both directions. To provide the system with redundancy and higher resolution, we use

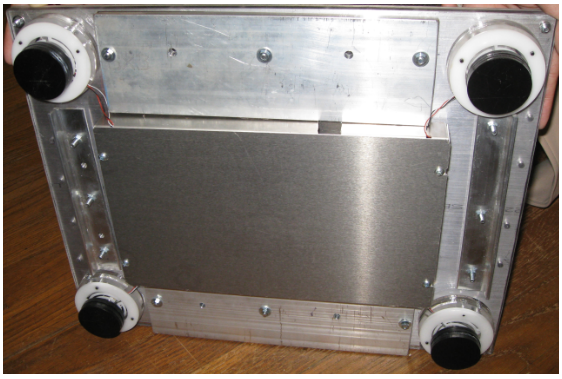

Figure 2: Bottom view of iBalance force platform.

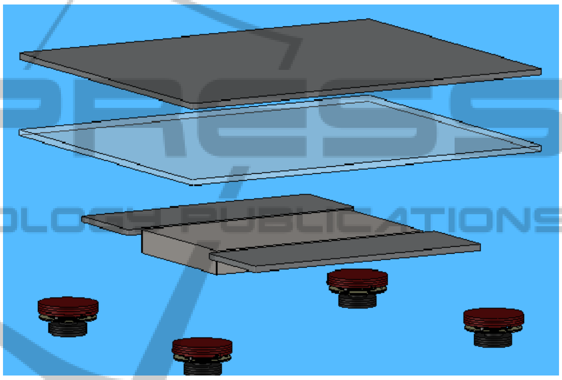

Figure 3: Exploding view of iBalance force platform.

four load cells placed under the corners of the platform. The load cells used in our prototype are similar to models used in bathroom scale devices.

Three designs were considered for the standing platform: a single platform (4 load cells per platform), a separate platform for each foot (2 load cells per platform), and a separate platform for each load cell. The different designs reflect a trade-off between platform

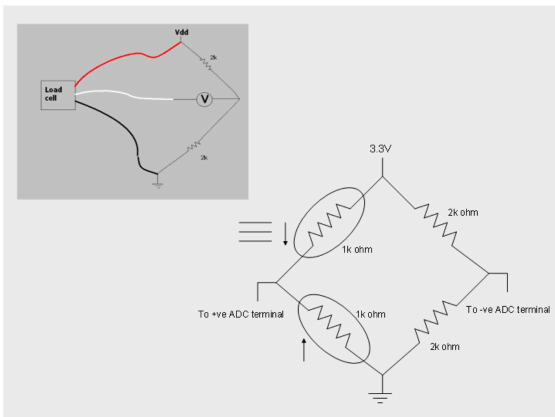

Figure 4: Design of load cells used in force platform.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

stability and measurement independence. The single platform provides the most stability, but all four pressure measures become correlated by virtue of the rigid platform, and torsion torque would not be measured. The two-platform design, consisting of one platform for each foot, would allow for detection of slight dorsiflexion or plantarflexion of the ankle. However, it would provide less stability as a platform. The single load cell platforms provide the least platform stability. We chose to use the single-platform design for its stability and sufficient sensitivity to the stabilometric properties measured by the software algorithm.

The load cell enclosures were designed to be flexible, since too much rigidity would cause a portion of the pressure to transfer directly from the platform to the floor rather than through the load cell. The flexible enclosure was constructed from laser-cut delrin and acrylic sheets. Aluminum bars were used to provide structure to the load cell enclosures. The load cells are rated at 75 kg each with a maximum of 150

2.2 Electronic Design

Load sensing is achieved with four off-the-shelf, three-wire half-bridge load cells, which is the most common configuration found in bathroom scales. The load cells are wired in a standard Wheatstone bridge configuration. Each load cell through its Wheatstone bridge sends voltage values to the analog-to-digital converter (AD7794 from Analog Devices) on different ADC input channels. This chip performs both signal amplification and conversion. The data acquired by the AD7794 is transmitted to an ATMega324 microcontroller over a serial peripheral interface (SPI). The microcontroller then sends this over USB to a computing device.

The AD7794 is a low-power analog front end for high precision measurement applications. The outputs from the four Wheatstone bridges are wired to differential input pins on the AD7794 development board. The AD7794 amplifies the difference between these pins, and then performs an A/D conversion. The results of the A/D conversion are made available to the ATMega324 microcontroller via the AD7794s communication protocol.

An ATMega324 development board is used to interface to the AD7794 development board. We used an off-the-shelf AVR development board with an ATMega324 microcontroller. This development board includes an on-board USB chip which allows the ATMega324 to easily stream data over USB. The ATMega324 development board uses a USB chip from FTDI to establish communications with a computing device. Drivers from FTDI were installed on the computing device, which makes the USB connection look like a COM port.

The firmware for ATMega324 performs the following general functions: using the SPI communication protocol, the ATMega324 communicates with the AD7794 to initiate each A/D conversion and read back the results. It then formats the resulting data into one channel, and streams the data out over the UART, which goes through a USB chip and out as a USB signal. The format of the data streamed is a repeating cycle through the 16-bit data from each load cell, serialized in clockwise order starting from the front left, followed by a series of padded zeros.

The AD7794 is programmed to continuously convert data at its maximum speed of 470 Hz. Due to multiple overheads in transmitting the data to the host machine, the transmission from one channel clocks in at 300 Hz, resulting in a frequency of 75 Hz for all 4 channels.

3 SOFTWARE DESIGN

The challenge in designing the software algorithm for the iBalance is to determine a suitable metric for reliably measuring change in an individual's balance profile over time. In order to be of practical use in the home or at the point of care, the metric used by the iBalance must also be able to be accurately derived from a relatively small amount of data.

Due to the complexity of the musculoskeletal and sensory mechanisms underlying balance, it is difficult to satisfactorily model the stability of an individual in terms of a deterministic physical model. A variety of standard techniques used to study balance instead consider the set of observations given by the time series of an individual's center of pressure during quiescent stance. The resulting time series gives rise to a large variety of metrics that may be used to quantify a balance state (Prieto et al., 1996) (Peterka, 2000). A few of the most widely studied include the peak-to-peak sway in the anterio-posterior and medio-lateral directions, the average velocity of the COP, and the power spectral density of the COP. Studies have shown that there are many redundancies in the full set of such metrics, from which a few principle parameters may be extracted (Rocchi et al., 2004). In this section we demonstrate that there are three principle groups of metrics, from which representative metrics may be extracted to form the basis of a singular parameter which can be used to track the balance profile of an individual over time.

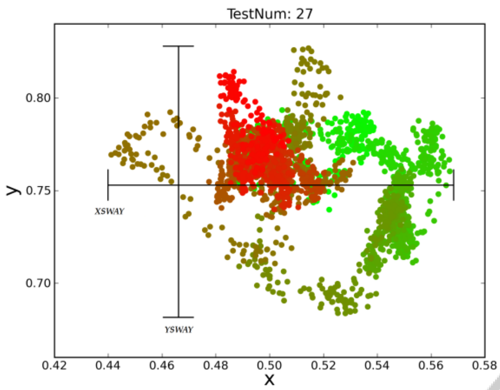

Figure 5: Sample stabilogram plot annotated with the medio-lateral peaksway (XSWAY) and anterior-posterior peaksway (YSWAY) metrics. The COP data time series is plotted relative to the coordinate axis of the force platform, with (0.5, 0.5) representing the center. The series is colored in progression from green to red over time.

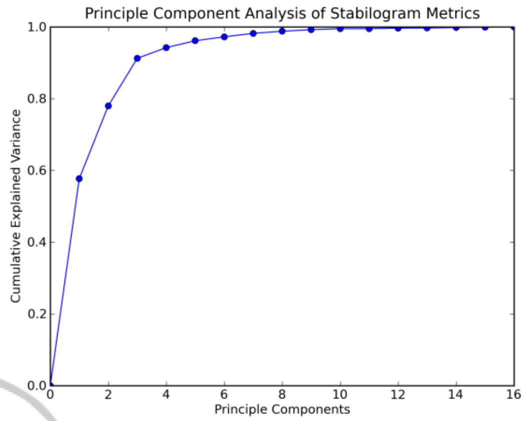

Figure 6: Normalized Cumulative Eigenvectors from Principle Component Analysis. The first three principle components account for approximately 58%, 78%, and 91% of the observed variation in the data.

SCITEPRESS
SCIENCE AND TECHNOLOGY PUBLICATIONS

3.1 Stabilometric Properties of COP Time Series

A large set of metrics have been reported in the literature that derive summary statistics from COP data (Prieto et al., 1996). Researchers have conducted Principle Component Analysis of different subsets of these metrics in an attempt to distill a standard combination with which stabilometric data may be analyzed (Prieto et al., 1996) (Rocchi et al., 2004).

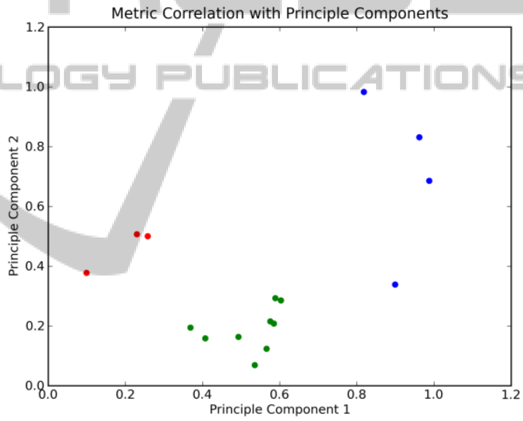

Figure 7: Correlation coefficients of each metric with first two principle components. The red, green, and blue datapoints correspond to Clusters 1, 2, and 3 listed in Table 1 respectively.

3.2 Principal Component Analysis of Astronaut Data

In constructing the iBalance algorithm, we are interested in how to derive a signal from the various stabilometric properties of the COP that maximally captures variations in the observed data. We conducted a principal component analysis on data from a group of individuals in both their normal and balance-compromised state. The particular dataset we chose to study was astronaut data generated by NASA. The effects of long-term exposure to zero-gravity conditions on the vestibular and musculoskeletal systems of astronauts is a heavily researched problem, and it is widely known that astronauts experience compromised balance during the first week upon their return from space, with variations in the recovery period differing among individuals.

For our analysis, we were able to use data collected from 18 NASA astronauts before launch and after return from space using NeuroCom International's dynamic posturography system. Center of pressure data was collected from each astronaut on 8 different occasions: 60, 30, and 10 days before launch, twice on return from launch, and 2, 4, and 8 days after launch. On each day of testing, three trials were performed under each of two standard NeuroCom protocols: SOT1 (quiescent standing, eyes open), and SOT2 (quiescent standing, eyes closed). The time series data collected from these trials were 20 seconds each in length, collected with a sampling rate of 100 Hz. The COP is represented as the relative normalized pressure in the medio-lateral and anterior-posterior directions, with (0.5,0.5) representing perfectly balanced pressure in each direction.

We follow the methodology of Rocchi et al in using the correlation matrix rather than the covariance matrix in the PCA due to the differences in parameter units and variance (Jolliffe, 1986). This prevents

Table 1: PCA shows that stabilometric properties derived from COP time series can be clustered into several distinct groups that correlate similarly with the observed principle components.

Cluster 1	MD	average Euclidean distance of the COP from mean normalized coordinates
	RMSD	root mean square value of the distance of COP from mean normalized coordinates
	YSWAY	maximum differential of coordinates along the anterior-posterior axis
	XSWAY	maximum differential of coordinates along the medio-lateral axis
	MAXD	maximum Euclidean distance of COP from mean normalized coordinates
	MV	mean velocity of COP with instantaneous velocity measured at 5 Hz
	RMSV	root mean square value of the velocity time series
	AREA-CC	area of circle centered at mean COP containing 95% of the observed COP time series, assuming Gaussian distr
	AREA-CE	area of ellipse centered at mean COP containing 95% of the observed COP time series, assuming Gaussian distr
Cluster 2	MFREQ	approximate rotational frequency in Hz of COP trajectory along circular path centered at the mean with radius equal to average distance from mean
	FDCC	fractal dimension of COP within 95% confidence circle
	FDCE	fractal dimension of COP within 95% confidence ellipse
Cluster 3	P50	median frequency, in Hz given by discrete fourier transform of COP time series
	P95	frequency below which 95% of total power is found, in Hz given by discrete fourier transform of COP time series
	FREQD	measure of variation in frequency content given by discrete fourier transform of COP time series
	CFREQ	measure of frequency at which power spectral density is most concentrated

the resulting principal components from being dominated by inherent differences in the variance of each parameter caused by differences in units. The results show that two principal components account for almost 80% of the variation in the data and three principal components account for more than 90% of the variation in the data. When we plot the correlation coefficients of each metric against the first two principal components, we see that the metrics naturally form three distinct clusters.

The first cluster corresponds to the metrics that are based on the length extent of the phase plot. This refers to measures of the overall size of the space traversed by the COP time series over a fixed interval of time. From a physical standpoint, this is analagous to measures of the maximum tilt from upright position an individual experiences over the course of the time series.

The second cluster corresponds to the metrics that are based on the area of the phase plot. This refers to measures of the total distance traversed by the COP time series over a fixed interval of time. Whereas the length extent of the phase plot only looks at maximum differentials between COP coordinates, the area measures look at how the space in between was filled. From a physical standpoint, this is analagous to understanding whether the subject was moving quickly or slowly within the fixed interval of the observed time series. In combination with the first cluster of metrics, we can gain an understanding of whether the subject was moving quickly over a small area, or moving slowly over a large area, or some other combination thereof.

The final cluster corresponds to metrics based on the power spectrum of the phase plot. This describes the frequency of oscillations observed in the COP time series. From a physical standpoint, analysis of the frequency domain may reveal underlying patterns in the feedback-control mechanism of the body as it attempts to maintain balance during quiescent standing, as well as any noise fluctuations caused by environmental factors that have an effect on balance.

See Table 1 for a list of metrics that belong to each cluster. These results show that we can use a representative metric from each of these clusters to determine a three-dimensional descriptive balance vector. The distance of this vector from the space of normal balance may be used as a singular metric describing the balance profile of an individual.

3.3 Punctuated Equilibrium Model of Human Balance

In addition to the metrics above, iShoe Research has developed a new quantitative and descriptive model for analyzing human balance which provides addi-

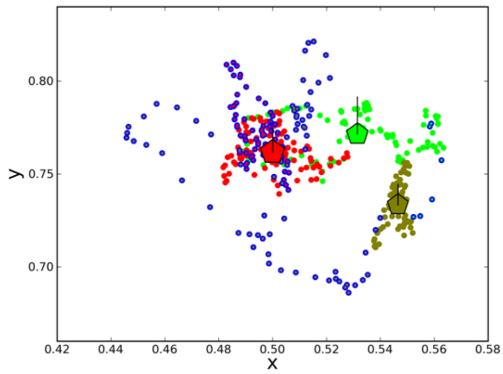

Figure 8: Stabilogram annotated with punctuated equilibria. The colored regions represent different clusters of static equilibrium, with overlayed pentagons indicating the relative size of the equilibria. The datapoints outlined in blue and black represent dynamic trajectories between different equilibria or returning to the same equilibria, respectively.

tional measures of an individual's stability. The Punctuated Equilibrium model captures the hypothesis that human balance can be characterized by two states: one of static equilibria, during which the center of mass remains stable within a bounded region, and one of dynamic trajectories, during which equilibrium is lost and the center of mass attempts to readjust to a new equilibrium. It is possible using Hidden Markov Model analysis to capture from the observed stabilogram data this underlying series of static equilibria punctuated by dynamic trajectories.

The Punctuated Equilibrium Model provides several quantitative measures for balance, including the number of equilibria, the length of time spent in each equilibrium, and the size of the bounded region for each equilibrium. For example, analysis of the NASA data described above shows a negative correlation between the number of equilibria and the quality of an astronaut's balance as represented by the number of days since return from space. In addition to these quantitative measures, the algorithm for Puncutated Equilibrium is also able to provide a qualitative visual model of an individual's balance profile. While stabilograms are typically difficult to analyze due to the density of datapoints collected in a bounded region over time, applying the algorithm for Punctuated Equilibria transforms the data into regions of stability and instability. The location and pattern of these equilibria and dynamic trajectories can help determine information such as whether an individual is weaker on one leg than the other or has a tendency to lean or fall in a particular direction.

4 GRAPHICAL USER INTERFACE FOR BALANCE RESEARCH

In order to facilitate the use of the iBalance as a research device, we developed a basic graphical user interface. The GUI is designed as a platform for data collection, as well as for providing analytic visualizations of the balance data.

4.1 Real Time Data Visualization

The GUI provides two methods for visualizing data in real-time as it is being collected from the iBalance platform. In the Stabilogram method, we display the real-time position of the subjects center of mass on a two-dimensional coordinate system. The display shows a trail of the previous second of movement, so any shift in position from the subject is immediately visually noticeable. The Oscilloscope method presents the same data in two simultaneous plots, displaying the time series of the center of mass in the mediolateral (ML) direction and in the anteroposterior (AP) direction. This second display highlights one-dimensional movements of the center of mass, and permits observation of the entire data collection sequence at any time. These real-time displays are updated at the same refresh rate as the hardware output.

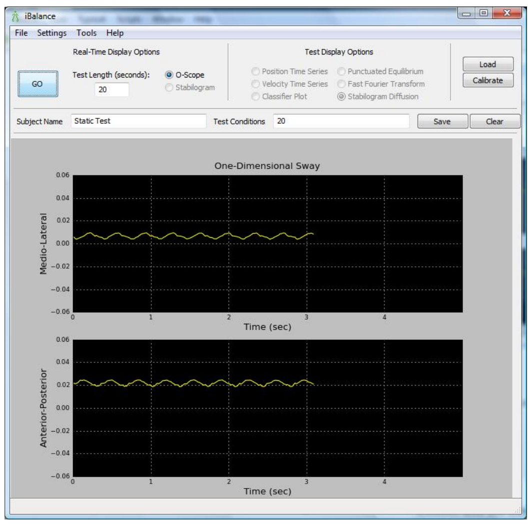

Figure 9: Oscilloscope view of real-time data collection from iBalance.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

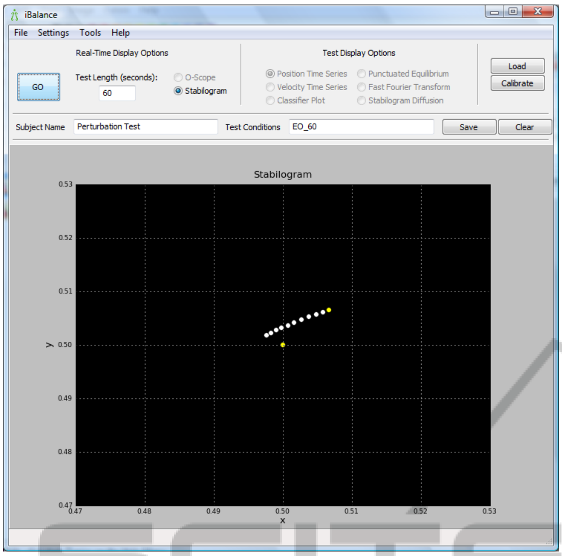

Figure 10: Stabilogram view of real-time data collection from iBalance.

4.2 Static Data Visualization

After data collection is complete, we provide additional methods for visualizing the resulting data. These methods are intended to provide summary statistics of the data, as well as to display the results of analysis using a variety of common as well as novel models for human balance. The two main models currently implemented for the GUI include the Stabilogram-Diffusion plot described by Collins and De Luca (Collins and De Luca, 1993), and the Punctuated Equilibrium analysis developed by iShoe Research. The GUI is designed to be easily extensible to use for visualization of COP data in the context of new models.

The existing options provide six display modes for the collected data. The Time Series option is similar to the real-time Stabilogram display, showing the subjects center of mass on a two-dimensional coordinate system. However, in the static display, the entire time series of data is displayed, and color transitions are used to denote the passage of time. The Velocity Time Series displays the magnitude and direction of the instantaneous velocity vector over the entire time series, using the same color transitions to show evolution of time. The Classifier Plot depicts the steps in the analysis of punctuated equilibria, which derives regions of stability and dynamic trajectories from the instantaneous velocity time series of the COP data using a Hidden Markov Model. The Punctuated Equilibrium plot visually displays the regions of equilibria computed by the HMM and the interspersed dynamic trajectories. The Fast Fourier Transform plot depicts the results of a Discrete Fourier Transform on the time series data. Finally, the Stabilogram Diffusion plot depicts the Stabilogram-Diffusion plot showing closed-loop and open-loop control described by Collins and De Luca (Collins and De Luca, 1993).

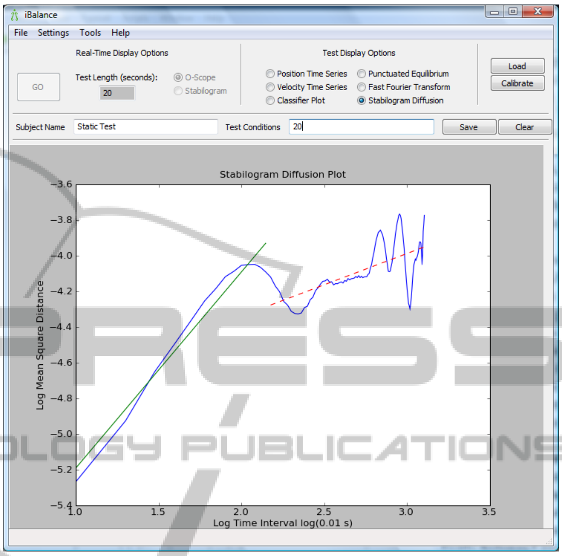

Figure 11: Stabilogram-Diffusion analysis (Collins and De Luca, 1993) of data collected from iBalance.

4.3 Data Collection

While we provide various forms of data visualization and provide access to our own Punctuated Equilibrium analysis, the primary purpose of the GUI is to be used as a platform for data collection. The GUI is designed to be easily extensible so that new approaches to analyzing the data can be incorporated into the toolkit by users. To this end, we provide functionality to output the raw data collected from the four load cells into comma-separated values (CSV) files. These are saved as raw 12-bit values. For the convenience of the researcher, we also write to the CSV file the derived center of mass coordinates in the AP and ML directions. Finally, the data files are automatically annotated upon creation to allow easy indexing of collected data.

5 CONCLUSIONS

With the high risk of falling in the senior citizen population and the significant health and financial costs of those falls, the benefits of preventative medicine for balance deterioration are clear. An effective solution

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

for long-term monitoring and early diagnosis of balance deterioration has the potential to be transformative for healthcare for senior citizens. The iBalance technology is a cost-effective platform for which both simple self-diagnostic algorithms as well as advanced clinical tools have been developed, with the hope that balance diagnostics will become as widely adopted as blood pressure monitoring to help prevent thousands of injuries each year. In fact, widespread use of the iBalance device and integrated GUI also has the potential to generate a wealth of data from which researchers may seek to gain a greater understanding of the variation in balance profiles between individuals and of the long-term progression of balance profiles in individuals.

Ongoing research for the iBalance aims to rigorously evaluate the accuracy and precision of the data collected by the hardware device in various environments, as well as validate the iBalance metrics against standard physical therapy balance measures through a prospective study with a blinded clinical trial. Areas for future work include refining the analytical algorithm to achieve the most valid and reliable results with the shortest data sample to increase its ease-of-use, as well as adapting analytical algorithms for use with pressure-sensing insoles worn throughout the day for continuous balance monitoring and measurement of dynamic gait.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. William H. Paloski of the Neurosciences Laboratory at Johnson Space Center for generously providing data from NASA for the study of balance metrics.

REFERENCES

Berg, K., Wood-Dauphinee, S., Williams, J., and Maki, B. (1992). Measuring balance in the elderly: Validation of an instrument. *Canadian Journal of Public Health*, 83 Suppl 2:S7–11.

CDCP (2009). *Falls Among Older Adults*. Centers for Disease Control and Prevention. Retrieved April 2009 from: www.cdc.gov/HomeandRecreationalSafety/Falls/adultfalls.html.

Chaudhry, H., Findley, T., Quigley, K., Bukiet, B., Ji, Z., Sims, T., and Maney, M. (2004). Measures of postural stability. *Journal of Rehabilitation Research and Development*, 41(5):713–720.

Collins, J. and De Luca, C. (1993). Open-loop and closed-loop control of posture: a random-walk analysis of center-of-pressure trajectories. *Experimental Brain Research*, 95:308–318.

Emery, C., Cassidy, J., Klassen, T. P., Rosychuk, R., and Rowe, B. (2005). Development of a clinical static and dynamic standing balance measurement tool appropriate for use in adolescents. *Physical Therapy*, 85(6):502–14.

Jolliffe, I. T. (1986). *Principal Component Analysis*. Springer-Verlag, New York.

Peterka, R. J. (2000). Postural control model interpretation of stabilogram diffusion analysis. *Biological Cybernetics*, 82(4):335–343.

Prieto, T. E., Myklebust, J. B., Hoffmann, R. G., Lovett, E. G., and Myklebust, B. M. (1996). Measures of postural steadiness: Differences between healthy young and elderly adults. *IEEE Transactions on Biomedical Engineering*, 43(9):956–966.

Rocchi, L., Chiari, L., and Cappello, A. (2004). Feature selection of stabilometric parameters based on principal component analysis. *Medical and Biological Engineering and Computing*, 42(1):71–79.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS