HERMES
Mobile Balance and Instability Assessment System

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Abstract: In this paper we introduce *Hermes*, a lightweight smart shoe and its supporting infrastructure aimed at extending instability analysis and human balance monitoring outside of a laboratory environment. By combining embedded sensing, signal processing and modeling techniques we create a scientific tool capable of quantifying high-level measures. The system monitors walking behavior and uses an instability assessment model to generate quantitative value with episodes of activity identified by the physician as important. The model incorporates variability and correlation of features extracted during ambulation that have been identified by geriatric motion study experts as precursors to instability, balance abnormality and possible fall risk. Our experiments demonstrate the feasibility of our model and the complimentary role our system can play by providing long-term monitoring of patients outside a hospital setting at a reduced cost, with greater user convenience, and inference capabilities that meet physicians and researchers needs.

1 INTRODUCTION

Fall related injuries are a growing challenge to health care systems. In 2002, more than 19 billion USD were spent on fall related injuries for those 65 and older in the US alone (J.A. Stevens and Miller, 2006). This number is expected to exceed 55 billion by 2020 (F. Englander and Terregrossa, 1996) (CDC, 2009). More astoundingly, the combination of direct and indirect costs related to fall related injuries range from 75 to 100 billion annually in the U.S (Comodore, 1995). A recent study shows that hospital and long-term-care costs resulting from falls in nursing homes and long term care facilities has been estimated to be an average of 6,200 per year per resident (N.V. Carroll and Narayanan, 2008).

Health care systems do not have the capabilities to continuously monitor an individual's instability and fall risk outside of a hospital setting. Although regular doctor visits are helpful, too many visits are required to be effective amounting to an enormous cost . In hopes of mitigating the economic and emotional costs of falls, we have developed *Hermes*. *Hermes* is a lightweight, non-invasive system that assesses a patient's fall risk through continuous monitoring in or outside of a lab setting. Although *Hermes* alone does not directly prevent falls, it does allow primary-care providers to make assessments

that could allow preventative measures to be taken. The current version of the *Hermes* prototype costs approximately $400. However, this cost can be reduced significantly when manufactured commercially.

To better understand the potential impacts of *Hermes* we present several methods currently used by physicians and geriatric experts for assessing instability and measuring imbalance. These methods are categorized into two major classes. The first set of methods are clinical tests that rely mainly on the trained eyes of physicians for evaluation and diagnosis (A. Behrman and Thigpen., 2002) (Upa, 1998) (Thorbahn and Newton, 1996). One benefit of this class of tests is that little or no equipment is required. The second major class of tests are those that occur in motion laboratories using expensive motion capture equipment along with pressure-based devices (Bertec.com, 2008) (Vicon.com, 2008) (Monsell, 1997) (Gaitrite.com, 2008). Consequently, these methods render highly quantitive and accurate results. With recent advances in embedded and wireless communication, a third class based on wearable and mobile platforms for balance and gait analysis has emerged. Low-cost, pressure-based systems like *Hermes* have been proposed for various health applications including foot ulcer prevention, fitness, and extrac-

tion of basic gait parameters (S. Bamberg and Paradiso, 2007) (F. Dabiri, 2008) (K. Maluf and Mueller, 2001).

The aforementioned clinical techniques and commercial systems lack quantitative and reproducible measures (such as those acquired through an electronic device) or are limited to a controlled environment (such as a lab) and only support short duration examinations. Even recent low-cost mobile alternatives lack data modeling techniques to properly assess instability and its progression.

Our system is motivated by (Maki, 1997) and recent findings in (Hausdorff, 2007) that show gait variability to be an effective measure of fall risk. However, the discussion of which gait parameters and how they vary is still an active discussion in the medical literature. For this reason, we designed *Hermes* to provide a gait analysis model configurable by health care professionals to meet their needs. This paper presents the following research contributions: 1) A mobile sensing platform (integrated within a shoe) that is non-invasive, customizable, low-power, and low-cost; (2) An instability assessment model that incorporates temporal and spatiotemporal factors to assess balance and instability; 3) Empirical study of Pedar (Novel.de, 2007) to model its behavior to be able to design such a system that can operate in low-power environment with lowcost components.

The remainder of this paper is organized as follows: In Section 2 we describe the systems architecture that comprise *Hermes*. Section 3 demonstrates our investigation on sensor selection and placement to minimize hardware and energy costs. Section 4 describes the signal processing used to extract temporal and spatiotemporal parameters in order to assess instability in human walk. Finally, we conclude the paper with section 5 and 6 by illustrating the feasibility of instability analysis model and discussing future work.

2 SYSTEMS ARCHITECTURE

Hermes is constructed with low-cost off the shelf sensors integrated within a shoe. We've integrated an Embedded computing platform to support data acquisition, synchronization and low-power radio communications. A smartphone with bluetooth and GPRS capabilities was used as a central aggregation and processing unit. Data is sent from the embedded device to the smartphone where its processed. Results are displayed to the user as well as propagated to a centralized server for further analysis and long term storage.

We used the MicroLEAP (L. Au and Kaiser, 2007) embedded sensing platform with bluetooth capabilties. Microleap contains an onboard 3-axis accelerometer and 3-axis gyroscope and connects to 7 external pressure sensors integrated within the shoe's insole (iden-
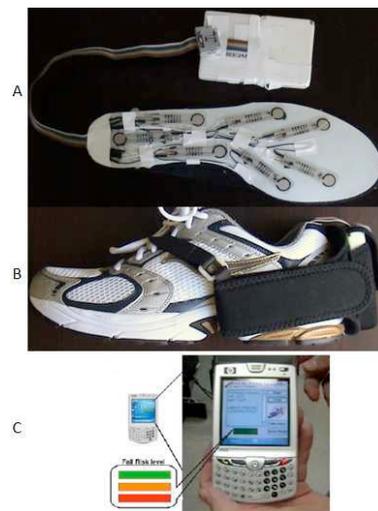

Figure 1: Hardware Architecture

tical setup on each shoe). The Microleap platform is mounted to the shoe's heel such that one axis of gyro and acceleration is aligned with the subjects body. All sensor data is collected with a 16-bit ADC.

3 SENSOR SELECTION

To get a better understanding of the signals resulting from the exertion of pressure by the feet we turned to Pedar (Novel.de, 2007). Pedar is an accurate and reliable pressure distribution measuring system for monitoring local loads between the foot and the shoe. It is comprised of insoles equipped with a grid of pressure sensors and a data acquisition unit capable of local storage and transmission to a PC over wireless or wired connection.

We utilized Pedar data acquired from 6 subjects. This data was analyzed to discern the variation of pressure distributions across individuals. This variation along with sensor correlations were used to significantly reduce the number of sensors, while still producing accurate calculations of gait parameters. This optimization lends itself to customizations at the hardware layer that can help to reduce cost and power of the mobile platform thereby making it more practical for day-to-day activity monitoring.

We make use of two key concepts from data modeling: *Variability* to provide information about the shape of the signal and how it is distributed and *Correlation* to provide information about how similar the shape (not amplitude) of the individual sensing channels are to one another. For our study we focused on using correlation to combine sensor readings which have similar shape and using variability to determine which sensors contributed most to the underlying phenomenon.

First we look into the correlation in the signals. Fig. 2 shows the correlation matrix for all 99 signals cap-
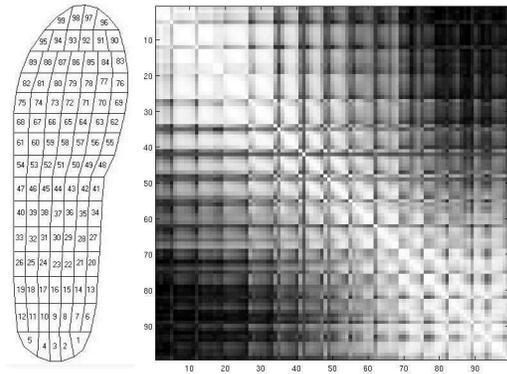
Figure 2: Correlation matrix of all 99 sensors in the insole of Pedar; the higher the correlation the lighter the color. The sensor mapping is shown on the left figure. The top left hand corner of the matrix is the heel region and the bottom right corner is the toe regions.

tured by Pedar. Unfortunately the correlation matrix is not useful by itself. To find the structure of the underlying data we turn to clustering. As with any clustering a similarity measure is needed to group the data points, for which we use correlation. In particular we take a graph-theoretic approach known as divisive (top-down) clustering to build a hierarchical structure which we then prune based on empirical measurements.
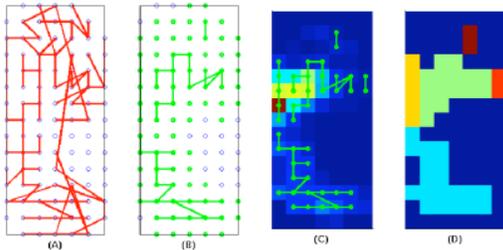

Figure 3: Clustering based on correlation and variance.

The first step in our approach is building a similarity graph, where nodes are sensors and edges are the correlations between sensors. Next we derive the minimal spanning tree similar to Fig. 3(A). We now use the minimal spanning tree as the baseline structure for divisive pruning and clustering. Due to the nature of spanning trees they most likely will have a combination of strong and weak links. To remove weak links we set an empirically derived threshold to obtain a tree similar to Fig. 3(B). A side-effect of such pruning is the creation of singleton clusters. To determine if our clusters (singleton or not) contribute significantly to the overall signal we use a second measure called variability. In Fig. 3(C) we have mapped the "pruned" spanning tree on top of a variance heat-map with lighter colors indicating greater variability in the sensing channel. Interesting enough most of the derived clusters fall within regions of high variability while smaller and singleton clusters fall in regions which contribute minimally to the overall signal.

This finding was verified across all the subjects. Finally using variability as a guide to prune unnecessary clusters we derive the final set of clusters as seen in Fig. 3(D).

The spanning tree itself provides insight into the structure of the data. As previously mentioned Fig. 3(A) shows the full minimum spanning tree. Some noticeable features are the horizontal and vertical connections. The horizontal connections indicate temporal consistency, meaning the shift of pressure from the back (heels) to the front (toes) is highly synchronized horizontally. The existence of vertical connections indicates spatial consistency as a result of a flatter application of pressure. Although many other factors influence correlation of the signals, here we want to show the higher-level inferences that can be derived from quantitative measures such as correlation.

As mentioned earlier, clustering is application dependent. The needs of the physician will dictate the number of sensors needed to output the interested statistics. In order to determine the correct number of clusters for our application we develop a loss function (criterion) as the average intra-cluster error and then empirically derived the cluster count, which minimized the criterion function.

Systems such as Pedar that have 99 sensors in the insole can measure desired parameters in all individuals since the sensors cover all the area under the feet. This is not the case in *Hermes* and other systems in wireless health since they have power and fidelity constrains. Therefore sensors placement needs to be customized for an individual user.

4 SIGNAL PROCESSING

Signal processing stack in Hermes is composed of preprocessing and processing stages. Signal conditioning, filtering and segmentation is part of preprocessing stage, while in processing stage temporal, spatiotemporal and consistency features are extracted based on which the measure for instability can be established.

We define the spatial and temporal parameters according to (Whittle, 2007) as following: Step length is the distance from a point of contact with the ground of one foot to the following occurrence of the same point of contact with the other foot. This can generally be thought of as the distance one foot moves forward in front of the other. Step time is the time taken for each step. Cadence is the number of steps taken per second. Stride length is defined as the distance between successive points of initial contact point of the same foot. It consists of two steps lengths, left and right. Gait speed is the product of stride length and cadence. Stance-to-swing ratio, where the stance phase is the time from heel-down to toe-off, and the swing phase is the time between toe-off and heel-down. Dual stance is the time

that both feet are in contact with the ground. Pressure correlation is the correlation of the pressures recorded in each step with the previous steps.

Temporal parameters are extracted through pressure signal analysis. The extraction of left and right stance phase, left and right swing phase, and dual-support phase features is done by by processing a minimum of four signals, which are most closely associated to the point of pressure for the toe and heel.

We process discretized and sanitized signals that represent the input pressure signals. These signals represent occurrences of *pressure-contact-on* and *pressure-contact-off*. Given these occurrences, we know exactly where the following occur: right heel on, right toe off, left heel on, and left toe off. For a single step cycle, these are the only events that we need to detect in order to generate all temporal features. Temporal features are calculated as follows: Left/Right stance phase is the time between the heel on and toe off, left/right swing phase is the time between toe off and heel on again, dual support is the time between right heel on and left toe off. Any other temporal parameter that is later decided to be useful, can be added in a similar manner.

Spatial parameters are extracted through both pressure and non pressure signal analysis. The signals acquired from pressure sensors are used to compute step consistency by computing the correlation of consecutive steps in real-time. We also use the signal reading from the accelerometer and gyroscope to compute the stride and step length using techniques described in (S. Bamberg and Paradiso, 2007).

Step consistency is calculated in real-time by computing the difference of two consecutive signals by taking the difference of their integral over the time according to Equation 1, where k is the operation window, S is the max number of steps taken, *es* and *bs* are the beginning and end point of the step and $P(x)$ is the function of recorded sensor value over the time. We keep track of the median difference over the window of 5 most recent steps ($K = 5$).

$$C = 1/k \sum_{i=S-k}^{S-1} (\int_{bs_{i+1}}^{es_{i+1}} P(t)dt - \int_{bs_i}^{es_i} P(t)dt) \quad (1)$$

The trend we define as the true behavior or activity that is observable. It is important to distinguish between trend and variance, trend is the true tendency of the variation, while the variance is deviation of the data from the trend. To develop our trend for a given data, we use a multi-pass interpolation with a predefined window to determine the relative average path.

Trend analysis is important because it is an accurate predictor of behavior. Accurate predictions of the behavior of a patient at any given time is a key component in the instability analysis model.

The next step in the data flow model is variance analysis. After the features are computed for each step cycle, and the trend function is computed for the signal in each segment, we compute the variability of each feature using equation 2, where p_i is the value of the features' variance relative to the trend as described in equation 3. γ is the trend function that is constructed as specified. If a patient is attempting to increase their speed, but are having difficulty doing so consistently, they are generally at a higher risk of falling. This is why the variance analysis is important for the instability model. In general, stronger variance in a feature implies a higher instability.

$$Var_{feature_k} = \sqrt{1/n - 1 \sum_{i=t}^{t+k} (p_i - \bar{p})^2} \quad (2)$$

$$p_i = s_i - \gamma(s_i) \quad (3)$$

Once the trends and the variability of each feature relative to trend is computed, for each feature the measure for instability can be established for each segment of input signal based on equation 4, where V_T and V_{ST} are the variance of temporal and spatiotemporal parameters in the segment. V_T and V_{ST} are computed based on equation 4, where τ_i is the variance of temporal feature i and σ_j is the variance of spatiotemporal feature j. α_i and γ_j are the coefficients which indicate the importance of a particular feature and they are constrained by equation 5. The coefficients can be set by physicians and domain exports to tailor the instability assessment to best fit an individual patient.

$$Instability = V_T + V_{ST} = \sum_{i=1}^{n} \alpha_i V_{\tau_i} + \sum_{j=1}^{m} \gamma_j V_{\sigma_j} \quad (4)$$

$$\sum_{i=1}^{n} \alpha_i + \sum_{j=1}^{m} \gamma_j = 1 \quad (5)$$

5 EXPERIMENTS

To determine the feasibility of our system to compute gait parameters and instability measure, for this paper we conducted experiments in both controlled and non controlled environments. A total of 6 individuals from our laboratory participated in the experiments. The test subjects were diverse in terms of height and weight and walking patterns; some were flat footed, others normal or slightly limping.

The first set of experiments has been conducted in the laboratory setting, while we placed our insole on top of Pedar's insole and asked our test subjects to walk and we compared the extracted gait parameters of *Hermes* and Pedar. For each parameter we compute the value

generated by *Hermes* vs Pedar and compute the error. Figure 4 shows our performance vs pedar based on aggregated error values of each feature for all trials among test subjects.
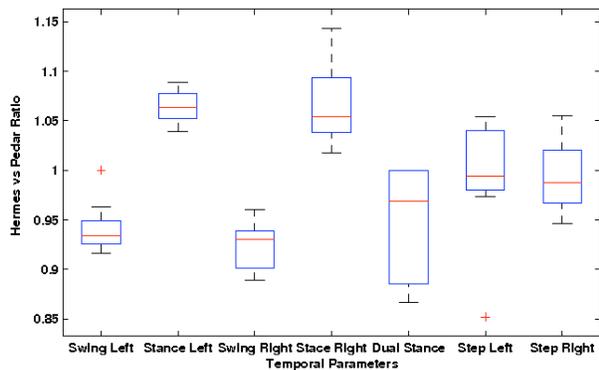

Figure 4: Accuracy of *Hermes* as compared to Pedar.

The second set of experiments was conducted in a non-controlled setting. Test subjects were instructed to take different paths and walk on different surfaces (such as flat, uphill and downhill) on our campus over 12 min episodes while performing various ambulation patterns in a one week period. Since feasibility was the primary goals of our experiments, in this paper, we focused on 3 patterns of normal walk (at constant speed), variable speed walk, and inconsistent walk. For each test subject, temporal and spatiotemporal parameters for each trial were extracted as explained in Section 4. Table 1 contains the corresponding variability analysis of the temporal features for each of the target ambulation patterns. The empirical distributions derived for gait parameters at various speeds indicates that *Hermes* is clearly sensitive enough to pick up variations at sub-1.75 Km/h granularity.

Table 1: Variance of Spatio-temporal features

Feature	Normal	Variable	Inconsistent
Stance Left	1.472	1.7351	3.76
Stance Right	1.0031	2.3119	4.1383
Swing Left	0.9849	0.906	1.757
Swing Right	1.336	2.3319	1.2321
S/R Ratio Right	0.0038	0.0081	0.0285
S/R Ratio Left	0.0050	0.0235	0.0153
Stride Right	2.7384	2.6353	7.364
Stride Left	2.0641	2.4066	7.0620
Step Right	1.3953	0.8247	2.7647
Step Left	1.2414	2.0733	2.0300
Dual Stance	0.5503	0.8884	0.667

A total of six temporal features were extracted as described in Section 4. Fig. 5 plots feature over time for the three different cases. First thing to note is the high

variability between feature for the inconsistent case relative to the two normal patterns. The variable speed graph also shows the need to consider trend in calculating the variance. The fact that the person slows down should not affect their balance as can be seen by the low variability around the trend.
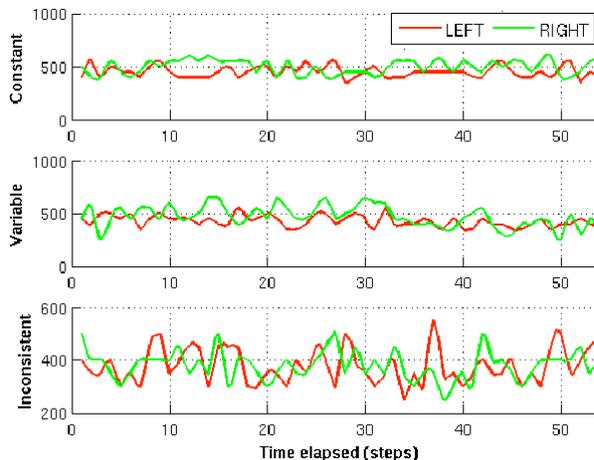

Figure 5: Swing phase variability with constant, variable and inconsistence speed. Variable speed shows a downward linear trend compare to that of constant speed, while inconsistent shows a relatively high variance.

Trend and variances were also computed for the temporal parameters across all three patterns. *Hermes* is able to compute the variance of each of the detected features by isolating the variability of the feature signal by taking the signals' trend into consideration. Fig. 6 illustrates how this is done for stance time. First the trend line is determined for the segment as shown in the top graphs. Then the trend is removed from the signal, as shown by the bottom graphs from which the variance is calculated. The resulting variances are shown in Table 1. To measure instability we asked our test subjects to walk with the three predefined ambulatory patterns. We then computed the instability factor for each of the patterns in the single set of activity. Fig. 7 shows the distribution of the instability measure for each of the episodes. The results verified the effectiveness of computed instability value. The instability factor for inconsistent walk is always higher than constant speed and variable speed walk, while the instability factor of variable speed walk is sometimes larger than constant speed and sometimes has the same value as constant speed. This is due to the fact that a part of variable speed also includes the speed of constant speed walk in our experiments.
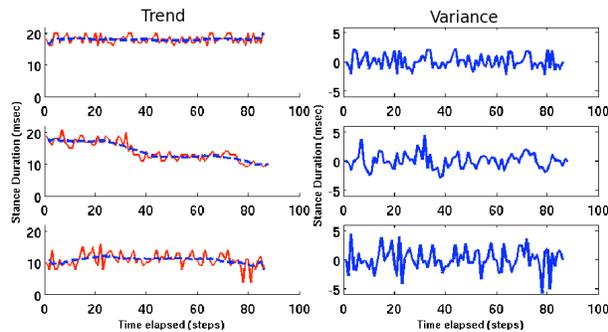
Figure 6: The trend and variance is calculated across three patterns of walking: constant speed, gradual speed change, and inconsistent walking.
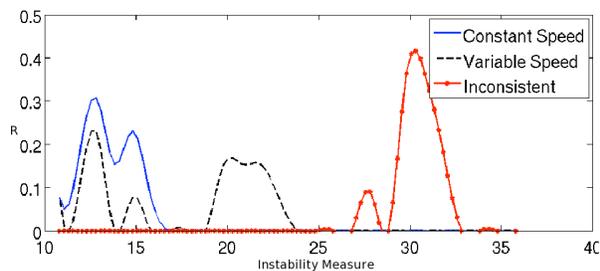

Figure 7: Empirical distributions of instability measure for one test subject performing the three walking patterns.

6 CONCLUSIONS AND FUTURE WORK

In this paper we introduced *Hermes*, a low-cost, customizable mobile platform capable of long-term instability and balance analysis for individuals who are prone to falling. This system aims to increase the physicians insight of patient walking patterns and behavior, which has generally been limited to ambulation analysis within hospitals and controlled environments such as gait labs. These day-to-day patterns and the variabilities associated with them are what our system is designed to detect. Through our system physicians, clinicians and researchers will be able to monitor and diagnose patient instability and balance over a long period of time.

For the future we plan to work closely with the medical community to get an approval for clinical study. We would like to test *Hermes* on real patients with various conditions and in different environments. Finally, We plan to enable the active feedback system on *Hermes*, both in hardware and software. We are also working to take advantage of external signals to provide a more sound instability measure, such as GPS data from the mobile device.

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