A Quiet Standing Index for Testing the Postural Sway of Healthy and Diabetic Adults Across a Range of Ages

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Abstract – A quiet standing index is developed for tracking the postural sway of healthy and diabetic adults over a range of ages. Several postural sway features are combined into a single composite feature, C, that increases with age, a. Sway features are sorted based on the r values of their linear regression models, and the composite feature is a weighted sum of sway features with optimal weighting coefficients determined using principal component analysis. A performance index based on both reliability and sensitivity is used to determine the optimal number of features. The features used to form C include power and distance metrics. The quiet standing index is a scalar that compares the composite feature C to a linear regression model $f(a)$ using $C'(a) = C/f(a)$. For a motionless subject $C' = 0$, and when the composite feature exactly matches the healthy control (HC) model $C' = 1$. Values of the $C' \gg 1$ represent excessive postural sway and may indicate impaired postural control. Diabetic neurologically intact subjects (DNI), nondiabetic peripheral neuropathy subjects (PN), and diabetic peripheral neuropathy subjects (DPN) were evaluated. The quiet standing indices of the PN and DPN groups showed a statistically significant increase over the HC group. Changes in the quiet standing index over time may be useful in identifying people with impaired balance who may be at an increased risk of falling.

Keywords: Quiet standing index, postural sway metrics, diabetes, peripheral neuropathy

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I. INTRODUCTION

The control of balance is a key aspect of mobility across the human life span from young children learning to stand and walk to elderly adults who may require the assistance of a cane or a walker. Postural control consists of both postural steadiness associated with the ability to maintain balance during quiet standing, and postural stability that is associated with the response to applied external stimuli and volitional postural movements [1]. The postural control system makes use of information from the visual, vestibular, and somatosensory systems [2]. There are many factors that potentially affect the postural control system and may lead to an increased risk of falling. These include health or medical conditions such as diabetes, peripheral neuropathy, stroke, multiple sclerosis, Parkinson's disease, and obesity, [3-5,15]. One of the most important determinants for the risk of falling is age [6-7]. As humans age, they experience reduced tactile and joint position sensitivity and increased reaction time [8], as well as reduced muscle mass [4].

Balance is achieved when the subject's center of gravity (COG) remains within the base of support. The COG is the vertical projection of the center of mass onto the base of support. It is a whole body characteristic that is difficult to directly measure, so typically the center of pressure (COP) is used instead. The COP is the location of the vertical ground reaction force vector on the surface upon which the subject stands. COP movements are used to control the horizontal displacements of the center of mass. In general the COP varies about the COG, with higher amplitude and higher frequency content [27]. During quiet standing on a single force plate, it is the net COP from both feet that is measured [9]. Over an extended period of time during quiet standing, the average of the COP must equal the average of the COG [28]. In quiet stance, humans invariably sway to maintain balance; and this motion is measured using the anterior-posterior (AP) and the medial-lateral (ML) components of the net COP. Different control mechanisms and different muscle groups of muscles are used to control AP and ML motion [27]. There are numerous metrics or features of quiet standing sway that have been measured and statistically analyzed including time-based, time and frequency-based (hybrid), and frequency-based characteristics [7,10-11]. In [1], the relative sensitivity, variation, and correlation of 13 groups of features was investigated, and this list of features was meant to be representative rather than exhaustive. More recently, the reliability of 36 COP features was analyzed in [12]. With so many quiet standing sway characteristics under consideration, there is no clear consensus as to which single metric or subset is most appropriate for describing the steadiness of young, old, healthy and unhealthy individuals.

This paper proposes a simple way to combine a set of quiet standing postural sway features into a single composite feature, C, that accounts for variation with age, a. The features are sorted based on the r values of their linear regression models. A weighted sum of selected sway features is used to form the composite feature with optimal weighting coefficients obtained using principal component analysis (PCA). Once a composite feature is defined, a linear regression model, $f(a)$, for healthy individuals can be created. The composite feature for an individual then can be compared with the healthy control (HC) model using a quiet standing index, $C'(a) = C/f(a)$. The quiet standing index takes on the value $C'(a) = 0$ when the subject is theoretically perfectly motionless (a state only approached asymptotically). In If the subject has a composite feature that exactly matches the healthy control model, then $C'(a) = 1$. Values of $C'(a)$ satisfying $C'(a) \gg 1$ indicate excessive postural sway and correspond to reduced steadiness. A combined reliability and sensitivity performance metric (described in Section III) is used to determine the optimal number of features for the composite feature C. Using prediction interval bands, the composite feature and quiet standing index of individuals can be compared with the healthy control group. An increase in the quiet standing index of an individual over time may indicate that the subject is beginning to experience a reduction in steadiness.

II. METHOD

A. Subjects and Testing Procedures

The initial set of subjects consisted of 108 adults ranging in age from 19 through 77 years. Thirty eight subjects were diagnosed by their primary care physicians with early mild type II diabetes. Ten of these diabetic subjects (DNI group) had normal peripheral nerve conduction velocity (NCV) tests, and the remaining 28 diabetic subjects were seen to have peripheral neuropathy (DPN group). Twenty two nondiabetic subjects were shown to have peripheral neuropathy (PN group). Thirty nine subjects, who were nondiabetic and neurological intact, constituted the healthy control (HC) group. The remaining nine subjects were not classified or used in this study because their minimum nerve conduction velocities fell within ± 2 % of the NCV thresholds for a finding of peripheral neuropathy. This elimination provided a clear border between the PN and non PN groups. The means of the physical characteristics of the groups of subjects under investigation are summarized in Table 1, where BMI denotes body mass index.

Group	Number	Age (year)	Height (m)	Weight (kg)	BMI (kg/m^2)
Healthy control (HC)	39	50.9	1.65	78.8	28.8
Diabetic, neurologically intact (DNI)	10	59.7	1.73	96.1	32.0
Nondiabetic with neuropathy (PN)	22	56.6	1.71	89.6	30.5
Diabetic peripheral neuropathy (DPN)	28	60.1	1.72	96.3	32.6
Total	99	55.7	1.70	88.2	30.7

Table 1: Mean physical characteristics of the groups of subjects under investigation

Histograms of the age distributions of the groups of subjects in Table 1 are shown in Figure 1 where it is clear that the three pathological groups tend to consist of older subjects. A majority of the subjects were recruited from the Veterans Administration (VA) Medical Centers in Shreveport, LA and Pittsburgh, PA (Highland Drive). The remaining subjects were recruited from the community by advertising at Louisiana Tech University and in the Shreveport area. The recruiting, screening, testing and informed consent procedures were reviewed and approved by the appropriate Institutional Review Boards.

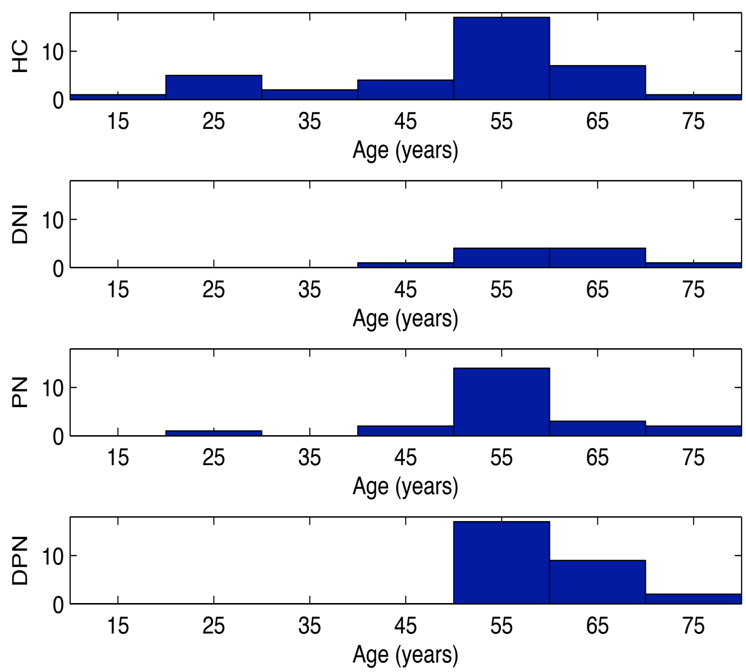

Figure 1: The age distributions of the 39 subjects in the healthy control (HC) group, the 10 subjects in the DNI group, the 22 subjects in the PN group and the 28 subjects in the DPN group.

The subjects that were recruited for this investigation all underwent visual, vestibular, auditory, musculoskeletal, and cognitive screening to maximize the liklihood that they had no undiagnosed conditions that may have affected their balance [13]. Subjects with respiratory dysfunction, cardiac condition, central nervous system disorder, musculoskeletal disorder, lower extremity amputation, severe arthritis, history of repeated falls, or that were currently taking medication to prevent dizziness were excluded.

The individuals with diabetes had mild type II diabetes as determined by their primary care physicians. All diabetic subjects had been diagnosed with diabetes within the past 10 years. They were using diet or oral medication to manage blood sugar levels, and they all reported stable blood sugar levels and acceptable hemoglobin A1C levels at the time of their testing.

Clinical nerve conduction tests on the lower extremities were performed by a VAMC technician under the supervision of a neurologist. The norms used to classify subjects were taken from the neurology department at the Pittsburgh VAMC. Nerve conduction velocity (NCV) tests were performed on the Tibeal, Peroneal, and Sural nerves of both legs, and the thresholds used were 41 m/s, 44 m/s, and 34 m/s, respectively. Each NCV was normalized by its threshold value, and the overall NCV score X was set to the minimum of the normalized velocities. Subjects were classified as belonging to the PN group when $X \leq 0.98$, the NI group when $X \geq 1.02$ and the $\pm 2\%$ gap when $.98 < X < 1.02$. It was felt that including a gap would give a more reliable classification in comparison with classifying every subject as either NI or PN, even when the NCV score fell right on the boundary.

The experimental data were obtained using the SLIP-FALLs system, sliding linear investigative platform for analyzing lower limb stability [14]. This is a computer-controlled air-bearing mobile platform instrumented with a force plate to precisely measure COP [14]. For this study the subjects stood barefoot on the platform, which was held motionless. Throughout the data collection, in the anterior-posterior (AP) direction subject's toes were aligned, and in the medial-lateral direction they were asked to take a normal width stance. In order to minimize the effects of visual and audio cues, the subjects were blindfolded, and headphones were used to provide masking noise (70 dB SPL) and instructions.

B. Quiet Standing Features

Quiet standing COP time-series measurements were taken for each subject. Here $x_{\mathrm{AP}}(k)$ and $x_{\mathrm{ML}}(k)$ denote the kth samples of the AP and ML components of the COP, respectively. Let f_s denote the sampling frequency, and let N denote the total number of samples. For this investigation, the sampling frequency was $f_s = 100$ Hz (after down-sampling by a factor of 10), and there were three quiet standing trials, each of duration 20 seconds. The first five seconds of each trial were removed to avoid potential start-up transients [22]. After removing the means, the data segments were joined using cubic splines to yield a single segment consisting of $N = 4500$ samples or 45 seconds [17]. This involved adjusting four points out of 4500 to avoid abrupt transitions at the segment boundaries. Since less than 0.09 % of the points were adjusted to fit the segments together, this appeared to have negligible effects on the computed features, all of which use some form of averaging.

For convenience, a plot of x_{AP} versus x_{ML} will be referred to as a stabilogram [1], also called a *statokinesigram* [28]. There are numerous metrics or *features* that can be used to characterize a stabilogram. A list of the 11 features considered in this case is shown in Table 2. The features in Table 2 are a subset of features defined in [1] and analyzed in [2]. To reduce the number of equations in the following feature definitions, let x denote x_{AP} or x_{ML}, as appropriate. Recalling that the means have been removed, the first two distance measures characterizing sway displacement are as follows:

$$\text{mean\_dist\_X} = \frac{1}{N}\sum_{k=1}^{N} |x(k)| \tag{1}$$

$$\text{rms\_dist\_X} = \left[\frac{1}{N}\sum_{k=1}^{N} x^2(k)\right]^{1/2} \tag{2}$$

The mean velocity characterizes the average speed of the sway and is computed by dividing the total distance traveled by the duration of the experimental run, $\tau = N/f_s$.

$$\text{mean\_vel\_X} = \frac{f_s}{N}\sum_{k=1}^{N-1} |x(k+1) - x(k)| \tag{3}$$

Three area measures have been proposed to approximate the area of the stabilogram. One measure, area_cc, represents the area the 95% confidence circle, a circle which is expected to enclose approximately 95% of the points on the stabilogram path. Another measure, area_ce, is somewhat more general in that it uses the 95% bivariate confidence ellipse. Computation of these two area measures is described in [1]. A third area measure estimates the area enclosed per unit time. It is constructed by summing the areas of the triangles formed by successive pairs of points on the sway path using the sway centroid as the third vertex [16].

The power measures of postural sway are based on the power density spectrum $S_x(i) = |X(i)|^2/N$ where $X(i) = \text{DFT}\{x(k)\}$ is the discrete Fourier transform. The average power is the average of the power density spectrum.

$$\text{ave\_power\_X} = \frac{1}{N}\sum_{i=1}^{N} S_x(i) \tag{4}$$

Each of the four groups of subjects in Table 1 was tested for outliers using the means of the features in Table 2. Subjects whose averaged more than 3.5 standard deviations from the mean were classified as outliers and removed. This resulted in two HC subjects, with mean deviations of +3.6 and +4.0, being removed. There were no outliers among the other three groups.

k	**Feature**	**Description**	**Type**	M_k	r_k	**Rank**
1	mean_dist_AP	mean distance AP (mm)	distance	1.83×10^1	0.224	2
2	mean_dist_ML	mean distance ML (mm)		1.61×10^1	−0.026	11
3	rms_dist_AP	RMS distance AP (mm)		2.37×10^1	0.207	3
4	rms_dist_ML	RMS distance ML (mm)		2.15×10^1	0.068	9
5	mean_vel_AP	mean velocity AP (mm/s)	velocity	6.27×10^2	0.056	10
6	mean_vel_ML	mean velocity ML (mm/s)		5.14×10^2	0.200	4
7	area_cc	area 95% conf. circle (mm^2)	area	1.43×10^4	0.173	5
8	area_ce	area 95% conf. ellipse (mm^2)		6.53×10^3	0.131	6
9	area_sway	sway area (mm^2)		2.97×10^3	0.121	7
10	ave_power_AP	average power (mm/samp.)	power	5.62×10^2	0.225	1
11	ave_power_ML	average power (mm/samp)		4.62×10^2	0.120	8

Table 2: Quiet standing postural sway features of 37 healthy adults, ages 19 through 77. For each feature, M_k is the maximum value, and r_k is r value of the linear regression model.

The set of features in Table 2 was selected using the following criteria. First, the feature value should go to zero when the subject is perfectly motionless. Second the feature value should increase when the size of the stabilogram increases. As a stabilogram grows in size, the center of gravity moves closer to the boundary of the base of support and the subject becomes less steady. Finally, the feature value should depend on all of the points in the stabilogram path in the sense that varying any point should vary the value. The first criterion eliminates fractal dimension and principal angle features because they are not well defined when the stabilogram is reduced to a point. The second criterion eliminates frequency features based on the shape of the power density spectrum because increasing the size of the stabilogram does not change, for example, the frequency centroid or the frequency dispersion. The third criterion eliminates range features because only the extreme points contribute to the range. It is also possible to have vector forms of the features listed in Table 2 such as the mean vector distance and the rms vector distance. These features were eliminated based on redundancy arguments because the two components of the position vector are AP and ML. By restricting the features under consideration to the $h = 11$ features listed in Table 2, the quiet standing index has a very simple physical interpretation that is easily understood and applied.

C. Feature Models

The last three columns of Table 2 were constructed using the HC group. Column five lists the maximum values of the features, M_k. To construct column six, the feature data were first normalized by M_k. For each feature, a linear regression model was fitted to the normalized data by regarding the feature to be a function of the subject's age, a. Here m_k is the slope and b_k is the intercept for feature k.

$$f_k(a) \quad = \quad m_k a + b_k \quad , \quad 1 \le k \le h \tag{5}$$

Column six of Table 2 lists the r value of the linear regression model. Here r_k^2 denotes the fraction of the total variance that is accounted for by the linear regression model and the sign of r_k is the sign of m_k [18]. The fact that the r_k values are quite small is an indication that the slopes are very small in comparison with the variance present in the data. A positive r_k indicates that the feature tends to increase with age. The results in Table 2 appear to be consistent with those reported in [1]. There a comparison of 20 healthy young adults with 20 healthy elderly adults showed that, for all features for which the two groups showed significant differences, the mean value increased for the older group. The last column in Table 2 is obtained by sorting the features based on decreasing values of r_k.

The candidate features in Table 2 will be reduced to the top $q = 3$ features listed in Table 3. The justification for selecting three features is based on a combined reliability and sensitivity performance metric that is introduced in Section III.

Number	**Name**	M_k	r_k	v_k	w_k
10	ave_power_AP	5.62×10^2	0.2248	0.5922	1.05×10^{-3}
1	mean_dist_AP	1.83×10^1	0.2241	0.5268	2.87×10^{-2}
3	rms_dist_AP	2.37×10^1	0.2070	0.6097	2.57×10^{-2}

Table 3: The features set S used for the composite feature C. M_k is the maximum value used for normalization, r_k is the r value of the linear regression model, v_k is the PCA weight, and w_k is the composite feature weight.

D. Composite Feature

The selected features in Table 3 can be combined into a single composite feature. Let g_k denote the kth selected feature. A *composite feature* is obtained by forming the following weighted average of q features.

$$C = \sum_{k=1}^{q} w_k g_k \tag{6}$$

The weighting coefficients are determined using a two-step process. First each feature g_k is normalized by dividing by its maximum value M_k. Normalization is useful because otherwise the composite value, C, can be more sensitive to features with large means and variances. Next a $q \times 1$ weight vector v is computed using principal component analysis (PCA) [26]. The weight vector w in (6) is then computed as $w_k = v_k/M_k$ for $1 \leq k \leq q$. The normalization factors, M_k, PCA weights, v_k, and composite feature weights, w_k, for the selected features are summarized in Table 3. Since PCA weights are used in (6), the composite feature is the first principal component of the data generated by the features in Table 3. The composite feature C accounts for 96.9 % of the total variance of the data using the features in Table 3.

By using a single composite feature, one can develop a test for steadiness. To see this, let a_i and C_i denote the age and composite feature, respectively, for subject i. Next let $f(a)$ be the linear regression model that fits the composite feature data, (a_i, C_i) for $1 \leq i \leq n$.

$$f(a) = ma + b \tag{7}$$

The composite features, C_i, and linear regression model, $f(a)$, for the HC group in Table 1 are shown in Figure 2. Also shown are prediction intervals [1] for the HC data, computed using

[1]Whereas confidence intervals predict a range for a *parameter* of the data, prediction intervals are meant to describe the data set itself. A 95% prediction interval is such that one would expect that 95% of the data points will fall within that interval.

a bootstrap method of [19], modified to account for linearly increasing standard deviation of the residuals. The shaded area represents the area between the 5th and the 95th percentile. The heavy solid line is the composite feature linear regression model for the healthy control group using the features in Table 3.

$$f(a) = 0.0027a + 0.4584 \tag{8}$$

The r value for the composite feature model, 0.2214, is relatively small because the slope is only $m = 0.0027$. In spite of this, as the age ranges from say 20 years to 80 years, this results is a 35.3 % change in the value of $f(a)$. From the spread in the prediction interval bands, it is evident that there is considerable variation in the composite feature data plotted in Figure 2. Note also that as the subjects grow older there appears to be more variation in the composite feature. The prediction intervals are important for properly interpreting the value of the composite feature. To illustrate this (using an extreme case), the data point for a 77 year old subject with a composite feature of $C = 0.98$ was shifted left and replotted as a solid marker associated with a 25 year old. Clearly the value of $C = 0.98$ lies far above the 95th percentile when it is attached to a younger individual, but it is just below the 90th percentile when evaluated at $a = 77$ years.

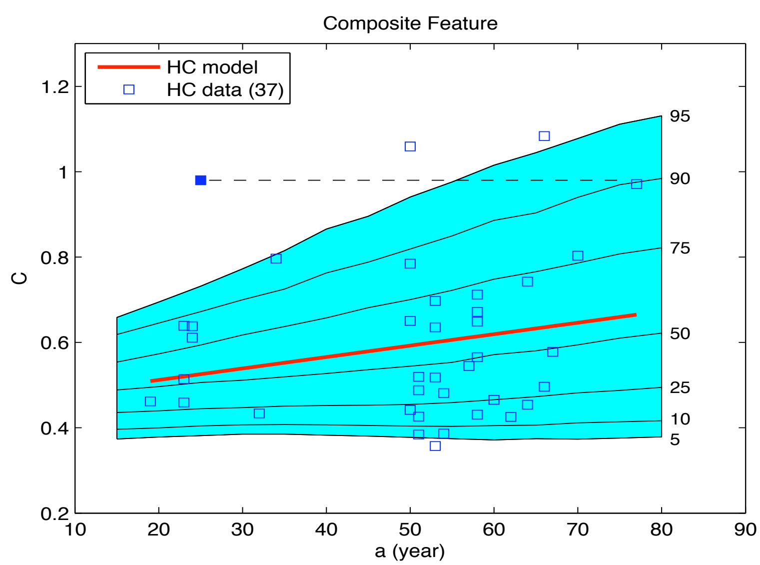

Figure 2: The composite feature C versus the age a for the subjects in the healthy control (HC) group. The solid line is the linear regression HC model $f(a)$. The shaded region represents the 5% to 95% prediction intervals for the composite features of the HC Group. The solid marker is moved left for illustration purposes.

Standard statistic:

As explained in this section (and amplified in Sec. IV), we have endeavored to show the thought process behind our definition of a composite feature. Although the weights shown in Table 3 might be altered by choosing a different (and/or larger) sample set, we are confident that those weights provide a *reasonable* way to average the various measures of quiet standing postural sway. As such, we define the *Composite SLIPFALLS Sway Statistic (CSSS)*, as the C value computed using those weights, with *Composite SLIPFALLS Sway Model* $f(a)$. If other researchers are interested in doing an "apples to apples" comparison with their own subjects, they should use these weights.

E. Quiet Standing Index

Given a healthy control model, the quiet standing characteristics of subjects can be compared to one another in two ways. The most direct approach is to use the *composite feature deviation.*

$$\Delta C(a) \quad = \quad C - f(a) \tag{9}$$

The prediction interval bands give an indication of how far above or below the healthy control model a composite feature falls. An alternative approach is to normalize the composite feature by the healthy control model to produce the following *quiet standing index.*

$$C'(a) \quad = \quad \frac{C}{f(a)} \tag{10}$$

Two values of $C'(a)$ have simple interpretations. The lower bound $C'(a) = 0$ occurs in the asymptotic limit when the subject exhibits no sway whatsoever. If the composite feature of a subject exactly matches the healthy control model, then $C'(a) = 1$. A plot of the quiet standing indices for the HC group is shown in Figure 3. The mean of the quiet stand index, by construction, is $\mu = 1$ and the standard deviation is $\sigma = 0.29$.

For the quiet standing index, values of $C'(a)$ satisfying $C'(a) \gg 1$ indicate excessive sway. When the amplitude of the sway is sufficiently large, the center of gravity of the subject moves outside the base of support in which case remedial action, such as movement of the feet or arms, is required to maintain balance. Consequently, very large values of the quiet standing index can be associated with a reduction in steadiness.

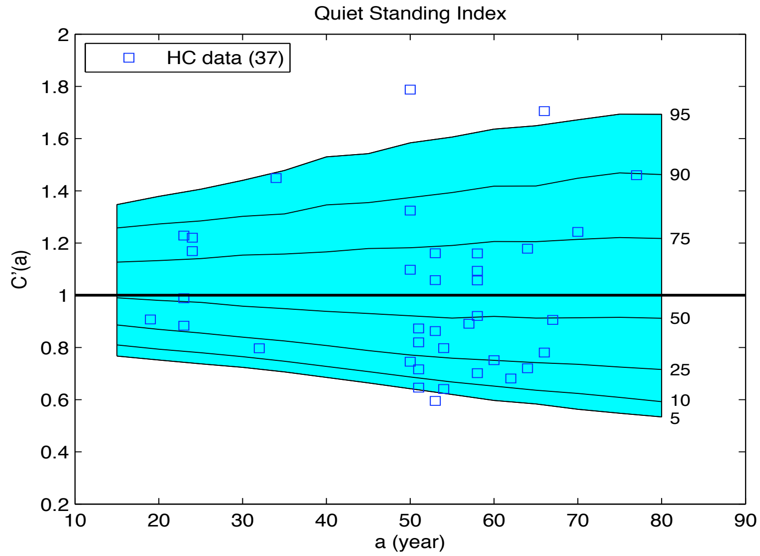

Figure 3: The quiet standing index $C'(a)$ versus age a for the subjects in the healthy control (HC) group. The solid line corresponds to the linear regression HC model. The shaded region represents the 5% to 95% prediction intervals for the quiet standing indices of the HC group.

III. RESULTS

A. Data Duration

The data used to compute the postural sway features were based on three epochs of quiet standing with eyes closed, each of duration 20 seconds. Five seconds were removed from the beginning of each trial to avoid startup transients [22]. The means of each segment were then removed and the segments were fitted together using cubic splines to produce a total of 45 seconds of postural sway data for each of the 99 subjects. The effects of the sampling duration on the value and the reliability of several individual postural sway features have been investigated [12,21,22]. These studies used data durations ranging from 10 seconds to 120 seconds with up to eight trials conducted either consecutively or over two days. The reported results for the optimal number and length of epochs ranged from one epoch of 20 to 30 seconds [21] to up to seven epochs of 60 seconds depending on the particular sway feature used [12]. In view of these findings, it is useful to examine how sensitive the composite feature is to the duration of the data used to compute it. Figure 4 shows a plot of the composite features of four subjects, selected at random from each group, as a function of the duration τ of the data used to compute C. The dotted vertical lines show the boundaries between the three epochs. For very short durations ($\tau \leq 20$) there can be considerable fluctuation in the C values. However, for longer durations ($\tau \geq 25$), the composite features begin to stabilize and are approximately flat. Consequently, to measure the composite feature, at least two epochs should be used. The fact that two to three epochs appear to suffice is perhaps a consequence of the fact that the composite feature C is based on a weighted average of several normalized features rather than on a single feature.

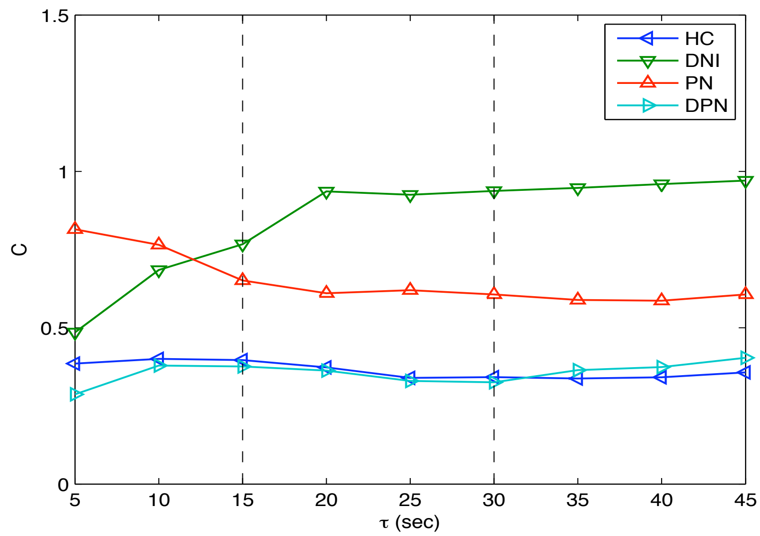

Figure 4: Composite features versus the data duration τ using random subjects from the healthy control (HC), diabetic (DNI), peripheral neuropathy (PN), and diabetic peripheral neuropathy (DPN) groups.

B. Subjects with Diabetes and Peripheral Neuropathy

Next it is of interest to examine the composite features and quiet standing indices of subjects who have been diagnosed with health conditions such as diabetes and/or peripheral neuropathy. The second group in Table 1 consists of subjects who are diabetic but neurologically intact (DNI). The composite features and quiet standing indices of the 10 DNI subjects are shown in Figure 5. In this case a few of the subjects exhibit an elevated quite standing index, but the results are roughly similar to those of the HC group. The mean quiet standing index for the DNI group was $\mu = 1.51$ and the standard deviation was $\sigma = 0.75$. Three subjects out of 10 fell above the 95th percentile band with one subject well above with a standing index of $C'(a) = 3.33$.

The third group of subjects in Table 1 includes individuals who have peripheral neuropathy but are not diabetic. The composite features and quiet standing indices of the 22 peripheral neuropathy (PN) subjects are shown in Figure 6. Seven of the 22 PN subjects exhibited quiet standing indices

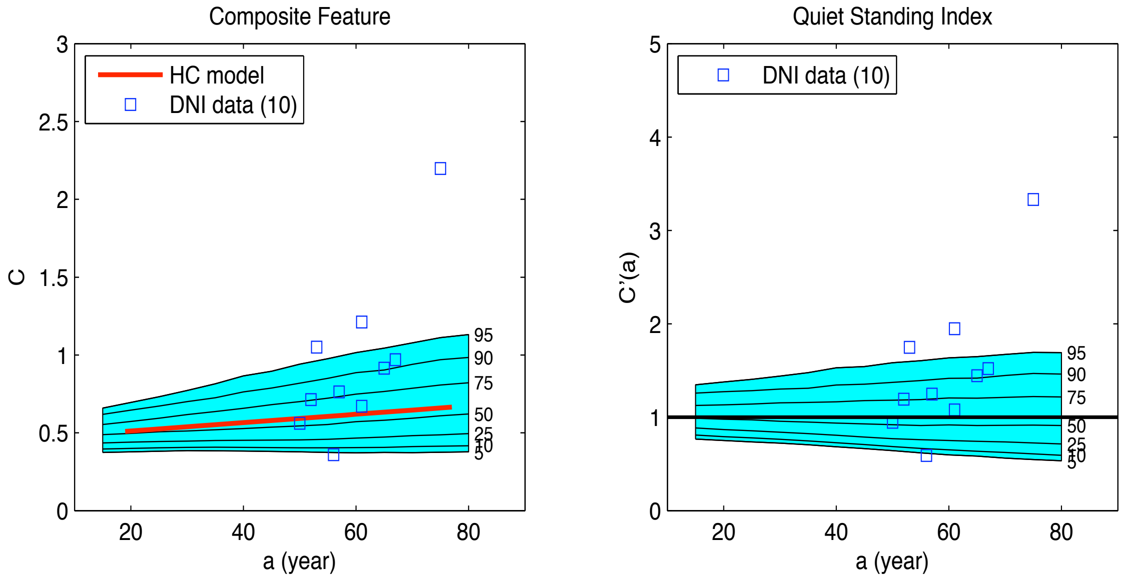

Figure 5: The composite feature C and quiet standing index C' versus age a for the 10 subjects in the diabetic (DNI) group. The solid lines correspond to the linear regression HC model. The shaded regions represent the 5% to 95% prediction intervals for the composite features and quiet standing indices of the HC group.

above the 95th percentile of the HC group with the largest being $C'(a) = 4.62$. The mean quiet standing index for this group was $\mu = 1.52$ and the standard deviation was $\sigma = 0.92$. It is evident that there is somewhat more variation in C and $C'(a)$ within the PN group.

The fourth group of subjects in Table 1 consists of individuals who are both diabetic and have peripheral neuropathy (DPN). The composite features and quiet standing indices of the 28 DPN subjects are shown in Figure 7. Nine of the 28 subjects had quiet standing indices above the 95th percentile of the HC group with the largest being $C'(a) = 3.82$. For the DPN subjects, the mean of the quiet standing index was $\mu = 1.52$ and the standard deviation was $\sigma = 0.71$.

C. Feature Set Selection

The feature set used for the composite feature C was arrived at using a two-step procedure. First, the features were sorted according to decreasing r values of their linear regression models. In this way, the effects of aging were taken into account. Next, the number of features, q, was chosen to ensure that the composite feature C is both reliable in terms of adding and subtracting features, and sensitive in terms of being able to distinguish between groups with different health characteristics. Let $C(i, q)$ be the composite feature of subject i using the first q features from the ordered list. As the number of features q increases, the ranking or relative position of healthy subjects based on their C values should not change or at least should exhibit minimal change. A

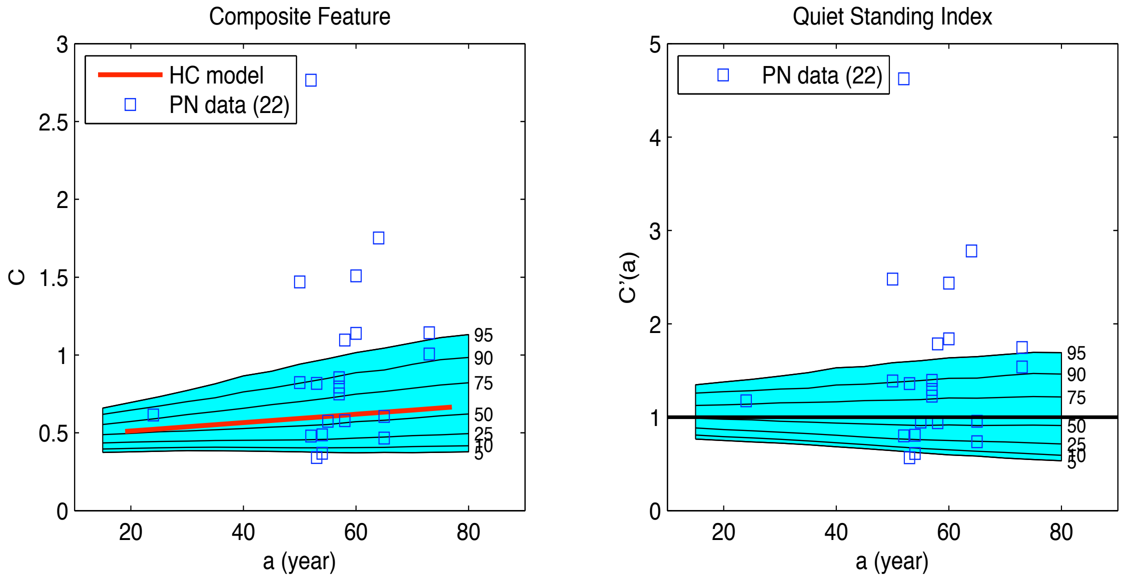

Figure 6: The composite feature C and quiet standing index C' versus age a for the 22 subjects in the peripheral neuropathy (PN) group. The solid lines correspond to the linear regression HC model. The shaded regions represent the 5% to 95% prediction intervals for the composite features and quiet standing indices of the HC group.

range of values for q over which the change appears to minimal can be determined by plotting the composite features $C(i, q)$ for the subjects in the HC group as shown in Figure 8. A careful viewing of this dense family of curves reveals a comb-like structure in the range $2 \leq q \leq 4$. The appearance of parallel lines means that for these subjects the values of C relative to one another do not change. Although Figure 8 contains considerable information, it can be difficult to analyze visually. The information in Figure 8 can be distilled to a single variable by examining how the ordering of the subjects changes with q. Since there are $n = 37$ subjects and $h = 11$ features, C is a $n \times h$ matrix. Let D be a sorted version of C using the MATLAB sort function.

```
[D,d] = sort(C);
```

Here each column of D contains the corresponding column of C, sorted according to increasing values of the composite feature. The qth column of the matrix d contains integers in the range 1 to n which show the ordering of the subjects based on their composite features when q features are used. In order to determine an optimal value for q, consider how the ordering of the subjects changes as the number of features changes. A significant change in the ordering of the subjects when a single feature is added or removed would suggest that the composite feature might not be reliable because its value would be highly sensitive to the addition or removal of a single feature. Using the information in d, let $i(q)$ be the number of positions or slots that contain a new subject

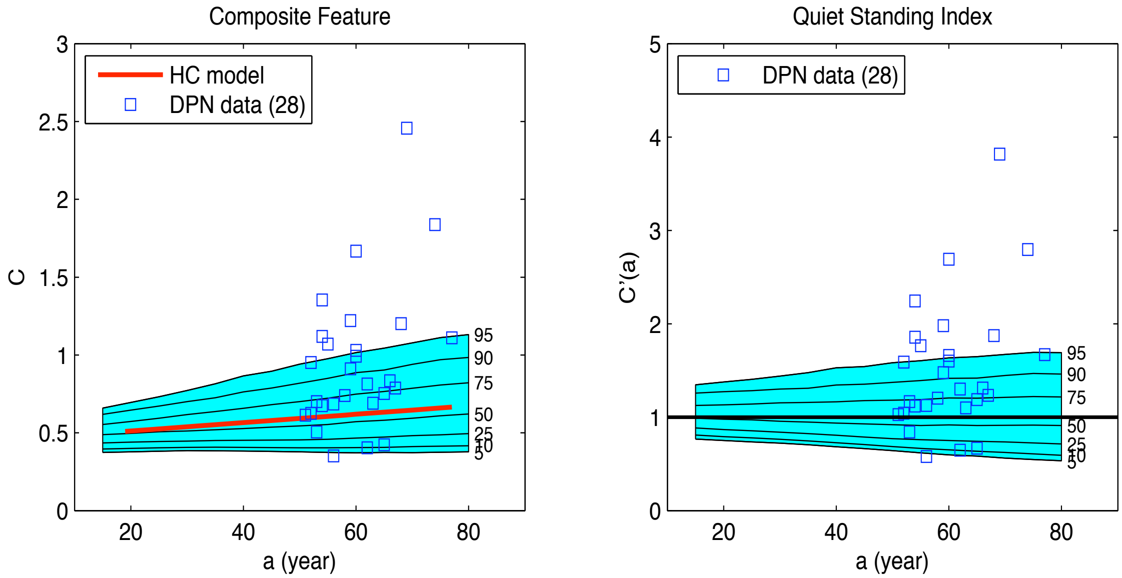

Figure 7: The composite feature C and quiet standing index C' versus age a for the 28 subjects in the diabetic peripheral neuropathy (DPN) group. The solid lines correspond to the linear regression HC model. The shaded regions represent the 5% to 95% prediction intervals for the composite features and quiet standing indices of the HC group.

as the number of features increases from q to $q+1$. Then the percentage of subjects whose ranking does not change is as follows where n is the number of subjects.

$$I(q) \quad = \quad 100 \left[1 - \frac{i(q)}{n}\right] \quad \% \tag{11}$$

Note that $I(q)$ ranges from 0 to 100 percent with 100 corresponding to the case when the ordering of the subjects based on C does not change as the number of features is increased from q to $q+1$. The measure in (11) represents the reliability of C over the interval $[q, q+1]$. In order to develop a reliability measure corresponding to the number of features q, one can take the average of $P(q-1)$ and $P(q)$.

$$R(q) \quad = \quad \frac{I(q-1) + I(q)}{2} \; \% \quad , \quad 1 < q < h \tag{12}$$

Note that $R(q)$ takes into account the effects of either adding or removing a feature from C. At the end point $q = 1$, no features can be removed so $R(1) = I(1)$, and when $q = h$ no features can be added so $R(h) = I(h)$.

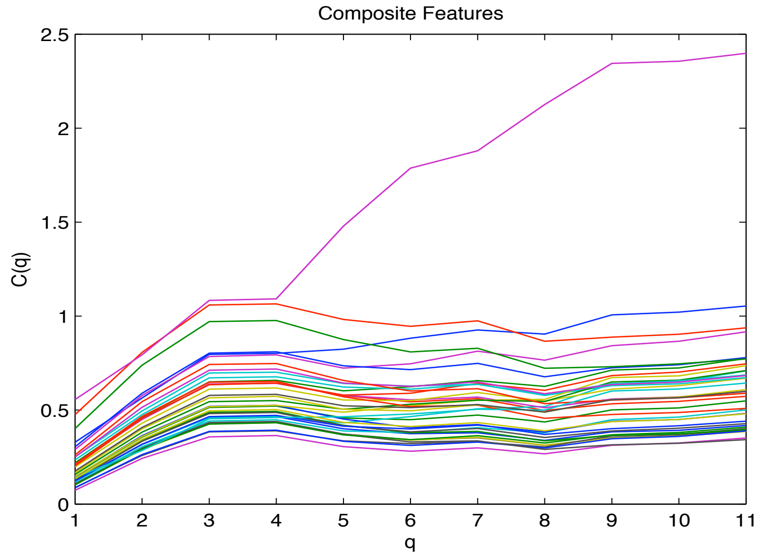

Figure 8: The Composite feature C versus the number of component features r for the 36 subjects in the healthy control (HC) group. The comb-like structure appearing in the interval $2 \leq q \leq 4$ represents a region where the relative ranking of subjects based on C does not change.

It is also useful to develop a quiet standing index that is sensitive in the sense that it is able to distinguish between different groups of individuals who may have health conditions that affect their balance. A one-wave analysis of variance (ANOVA) was performed on the four groups. Given the null hypothesis that there is no statistically significant difference between the means of the groups, the p value specifies the probability that the null hypothesis is true. Let $P(q)$ be the p value using q features to form the quiet standing index. Then the number of features at which the quiet standing index is most sensitive corresponds to the minimum value of $P(q)$.

The two characteristics, reliability and sensitivity, can be combined using the following performance metric which is a function of the number of features q.

$$V(q) \quad = \quad \left(\frac{P_{\min}}{R_{\max}}\right)\frac{R(q)}{P(q)} \quad , \quad 1 \leq q \leq h \tag{13}$$

Here $R_{max} = 70.3$ % is the maximum value achieved by the reliability measure, while $P_{\min} = 0.0038$ is the minimum value achieved by the sensitivity measure. If $R(q)$ and $p(q)$ were to achieve their extrema at the same number of features, then the peak value of the combined performance metric $V(q)$ would be one. A plot of the performance metric $V(q)$ is shown in Figure 10. There is a peak at $V(3) = 0.90$ thus confirming how the $q = 3$ features previously listed in Table 3 were chosen.

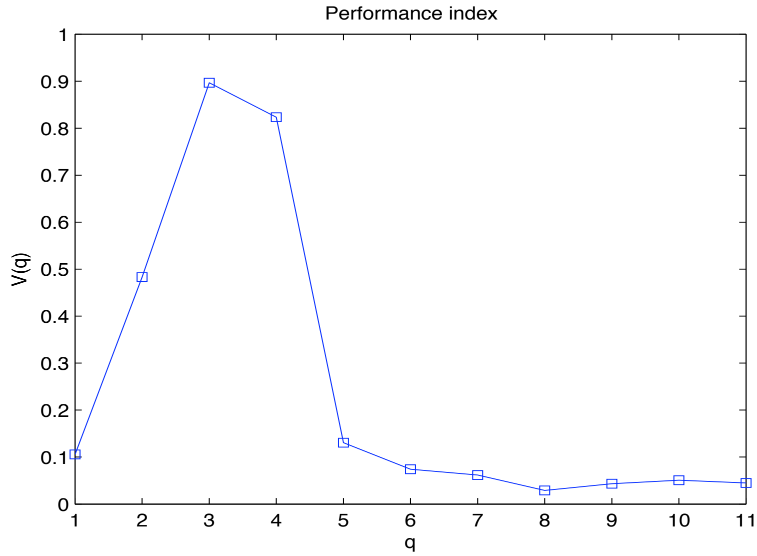

Figure 9: The performance index $V(q)$ which takes into account the reliability of adding or subtracting features and the sensitivity in distinguishing between different groups of subjects.

The three features summarized in Table 3 include one power feature (ave_power_AP), and two distance features (mean_dist_AP and rms_dist_AP). The average power feature uses information contained in the power density spectrum, and it does so with a metric that goes to zero when the subject is motionless and increases in value as the size of the stabilogram increases. Using both mean distance and rms distance provides for applying different importance values for outlier type motion. Note that the performance in Figure 9 is almost is high when $q = 4$ features are used. Including the fourth feature, mean_vel_ML, would add not only another type of feature (velocity) but also another direction (ML). However, when $q = 4$ features are used, the PCA weight for mean_vel_ML is only $v_4 = 0.042$. This is a full order of magnitude smaller than the other PCA weights thus suggesting that mean_vel_ML does not contribute significantly to the C. The fifth feature is area_cc, and with it all four groups of features from Table 2 would be represented. However it is clear from Figure 9 that when five features are used the performance decreases to a value that is only marginally better than that achieved using a single feature. Note from Figure 9 that when three features are used, the performance is 8.5 times higher than the performance obtained using a single feature. In our view of sway as a mechanical realization of the control mechanism, we would argue that these measures are likely to capture the relevant information. We expect that the composite sway provides a generalized measure of "amplitude of sway."

D. Ability to Discriminate

A one-way ANOVA of the quiet standing indices of the four groups was performed in order to test the ability of C' to discriminate between the groups. It should be noted (Figure 1) that the HC group contains more young subjects than the other groups. The results indicated that the quiet standing index did detect a statistically significant difference between the four groups of subjects with a p value of $p = 0.0038$. A multiple comparison was then made to see how the means of the groups differed from one another with the results shown in Figure 10.

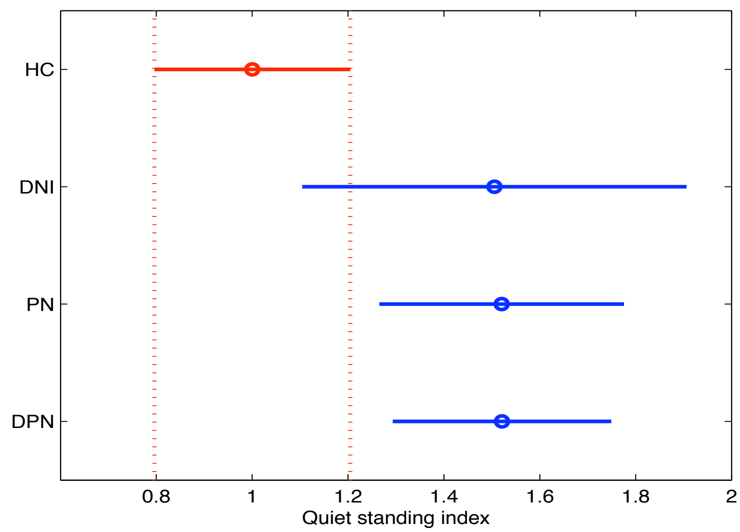

Figure 10: A multiple comparison of the quiet standing indices of the four groups of subjects. There is a significant increase in the mean of the PN group in comparison with the mean of the HC group since the 95 percent confidence intervals do not overlap.

Both the PN subjects and the DPN subjects showed a statistically significant increase in the quiet standing index in comparison with the HC group where it can be seen that the 95 percent confidence intervals do not overlap. By contrast, the neurologically intact diabetic subjects (DNI) did not show a significant increase in the mean of the quiet standing index at the 95 percent confidence level. This may be due, at least in part, to the fact that the DNI group was less than half the size of the other groups. In addition, all of the subjects were in relatively good health with no history of falls. Subjects with diabetes were stable with well-controlled H1AC levels. Additionally, all subjects had high scores on the Berg Balance Scale (BBS), a clinical measure of balance [22-23]. The lowest score on the BBS in any of the four groups was 53/56. The fact that PN and DPN subjects appeared less steady makes sense in terms of the underlying postural control system. Low nerve conduction velocities mean more delay in the feedback control system used to maintain balance. It is well known that as delay is increased in a linear feedback control system, the stability margin decreases [25].

A summary of the quiet standing index characteristics of the four groups is shown in Table 4. For each group, the increase in the mean quiet standing index was influenced by individuals whose quiet standing indices fell above the 95th percentile of the HC group. The last column in Table 4 shows the percentage of subjects within each group whose C' values were above the 95th percentile of the HC group.

Group	n	μ	σ	$C' > 95\%$
Healthy control (HC)	37	1.00	0.29	5.6 %
Diabetic, neurologically intact (DNI)	10	1.51	0.75	30.0 %
Nondiabetic, peripheral neuropathy (PN)	22	1.52	0.92	31.8 %
Diabetic peripheral neuropathy (DPN)	28	1.52	0.71	32.1 %

Table 4: Quiet standing index characteristics of the groups of subjects. Here n is the number of subjects, μ is the mean, σ is the standard deviation, and $C' > 95\%$ is the percent of subjects that lie above the 95th percentile of the HC group.

IV. DISCUSSION

There are several novel characteristics that set the composite feature and quiet standing index apart from other postural sway metrics that have been proposed. The first is the technique used to sort the individual sway features based on their sensitivity to age using the r values of their linear regression models. An alternative way to select features was introduced in [24] and applied in [5]. Here 14 postural sway features commonly used in clinical practice were analyzed using principal component analysis (PCA). For 19 Parkinson's disease subjects in the levodopa off state, it was found that the first four principal components (weighted sums of the 14 features) were sufficient to account for 94.7 % of the total variation in the data. The individual sway features with the most significant contributions to each of the principal components were then identified using a process described in [24]. A similar analysis was applied to the Parkinson's disease subjects in the levodopa on state where it was found that the first three principal components (different from the off state) account for 93.0 % of the total variation in the data. Using this technique, significant groups of sway features were identified, and individual features were ordered or ranked within each group. This is in contrast to the proposed approach where all features are initially ranked with respect to their sensitivity to age using the r values of their linear regression models.

The second unique characteristic of the composite feature C is the determination of an optimal number of individual sway features. For each fixed number of features q for $1 \leq q \leq h$, a PCA was used to compute optimal weights. The composite feature C corresponds to the first principal component and it accounts for the maximum variance in the data. For each q, the subjects were sorted according to increasing values of C. To determine the optimal number of features, the sensitivity of the ordering to changes in the number of features was computed. This led to a reliability measure $R(q)$ that specifies the percentage of subjects whose position, in the sorted list, does not change when a feature is added or removed. Thus $R(q)$ represents the reliability of using C to rank the subjects. The sensitivity of the quiet standing index $C'(a)$ in being able to distinguish between groups of subjects with different health characteristics was also examined by computing the p value, $P(q)$, using a one-way ANOVA. These two characteristics, reliability and sensitivity, were then combined into a single performance metric $V(q)$ whose peak value was used to determine the optimal number of features. The optimum of $q = 3$ features achieved a reliability of R(3) = 70.3 % and a sensitivity of $P(3) = 0.0038$. In [5], the number of individual features was fixed at $q = 14$ and the number of principal components was allowed to vary until at least 90 % of the variance was account for. For the composite feature C, the number of principal components is fixed at one, but the number of individual features that contribute to it was allowed to vary, and it was found that the optimal number from the sorted list was $q = 3$. The composite feature C accounts for 96.9 % of the total variance in the data associated with the selected features.

A third novel characteristic of the quiet standing index is that is explicitly incorporates the effects of aging. Using the composite feature C, a linear regression model was developed for HC subjects that shows how the composite features varies with age. Normalization of the composite feature by the HC model than yields the quiet standing index, $C'(a)$, a postural sway metric that takes the age of the subject into account. Prediction interval bands that show the percentiles of HC subjects who are expected to have C and C' values below a given threshold were also computed. These prediction interval bands can be used in a fashion similar to the clinical growth charts that physicians use to chart the development of children as their height and weight change with age as they mature.

In most of the studies of postural sway, analysis of quiet standing for an individual has been viewed in relation to a larger sample group. In a clinical setting, there is only one sample — the person being tested. To evaluate the result of such a COP measurement requires an understanding of the "normal range," where a number of studies indicates that this *normal* should vary with age. In particular, we note that a sway value that might be "healthy" for an elderly patient could be viewed as "excessive" for a young adult (e.g., see dashed line in Figure 2). Similarly, our model attempts to distinguish between normal growth of sway due to aging and the excessive growth of sway that might indicate a true postural instability, with the composite feature C providing an absolute assessment of stability (which degrades with age), while the sway index C' provides an age-relative assessment. Our methodology provides a means for evaluation of these single sample points without requiring a direct comparison group.

The composite feature and the quiet standing index may be useful clinical tools to assess balance dysfunction when working with individuals with balance disorders. The quiet standing index combines several different postural sway characteristics into a single scalar score, C', that is easily understood by both clinicians and patients. Figure 10 shows that this score is able to distinguish between adults with balance impairment and adults without balance deficits. The quiet standing index may also be more sensitive to change after rehabilitation than other measures. However, further research is necessary to evaluate that hypothesis. Applying the quiet standing index to other patient populations would also be an area for further research. As previously noted, we assert that the weighting coefficients of Table 3 and the model of (8) provide a reasoned way to express a composite feature, and researchers/clinicians interested in applying this technique should use these values in computing the CSSS. However, the prediction intervals (which help to describe what is normal, marginal, or outlier) would benefit from additional data on healthy individuals. Prediction intervals based on the bootstrap method in [19] for the composite feature C and the quiet standing index C' are summarized in Table 5 and Table 6, respectively. We expect to refine the curves defined in Tables 5 and 6 as more data become available.

Age	**Percentile**						
(year)	**5**	**10**	**25**	**50**	**75**	**90**	**95**
15	0.380	0.402	0.442	0.494	0.559	0.620	0.660
20	0.387	0.408	0.448	0.504	0.581	0.649	0.697
25	0.390	0.411	0.451	0.510	0.602	0.680	0.740
30	0.392	0.413	0.453	0.515	0.623	0.706	0.778
35	0.390	0.412	0.453	0.520	0.645	0.735	0.823
40	0.391	0.414	0.458	0.528	0.666	0.763	0.858
45	0.388	0.413	0.459	0.536	0.690	0.797	0.906
50	0.382	0.409	0.462	0.549	0.714	0.828	0.951
55	0.382	0.409	0.464	0.556	0.737	0.860	0.988
60	0.379	0.409	0.470	0.568	0.758	0.893	1.029
65	0.373	0.408	0.474	0.576	0.773	0.921	1.062
70	0.376	0.411	0.481	0.594	0.795	0.947	1.083
75	0.376	0.413	0.487	0.608	0.814	0.974	1.123
80	0.379	0.419	0.497	0.619	0.833	0.997	1.144

Table 5: Bootstrap prediction intervals for the composite feature C using the healthy control (HC) subjects

Age (year)	Percentile						
	5	**10**	**25**	**50**	**75**	**90**	**95**
15	0.770	0.811	0.889	0.989	1.122	1.247	1.335
20	0.761	0.800	0.876	0.983	1.136	1.267	1.366
25	0.746	0.785	0.859	0.968	1.143	1.288	1.409
30	0.729	0.768	0.840	0.953	1.152	1.301	1.437
35	0.709	0.747	0.821	0.939	1.160	1.316	1.479
40	0.691	0.733	0.809	0.931	1.170	1.332	1.501
45	0.670	0.713	0.791	0.922	1.180	1.356	1.545
50	0.644	0.688	0.776	0.920	1.193	1.377	1.586
55	0.626	0.671	0.760	0.910	1.202	1.396	1.610
60	0.604	0.653	0.750	0.908	1.210	1.420	1.644
65	0.577	0.632	0.736	0.899	1.210	1.435	1.664
70	0.562	0.619	0.726	0.905	1.219	1.449	1.668
75	0.543	0.601	0.718	0.905	1.219	1.466	1.700
80	0.528	0.590	0.712	0.901	1.224	1.475	1.701

Table 6: Bootstrap prediction intervals for the quiet standing index C' using the healthy control (HC) subjects

One of the useful characteristics of the power and distance metrics used to form the composite feature is that they all can be computed in real time. All of the features in Table 2 assume that the means of the COP data have been removed. The mean itself can be computed in real time using the following recursive formulation for the mean of the first k samples. Here $\mu(0) = 0$.

$$\mu(k) = \left(\frac{k-1}{k}\right)\mu(k-1) + \frac{x(k)}{k} \quad , \qquad k \geq 1 \tag{14}$$

By using a real time formulation of C', a subject can be evaluated using a single quiet standing trial, blind folded and lasting up to perhaps 60 seconds. The measured value of C' can be displayed and it should stabilize once sufficient time has elapsed.

Subjects were classified into groups that included diabetic and neurologically intact (DNI), nondiabetic with peripheral neuropathy (PN), and diabetic with peripheral neuropathy (DPN). In each case the percentage of subjects with C' values above the 95th percentile band of the HC group was approximately six times that of the HC group. Using an ANOVA, the quiet standing indices of the PN and DPN groups showed statistically significant increases over the HC group. The smaller DNI group did not show a statistically significant increase at the 95 % confidence level. Besides comparing groups with different physical characteristics, the quiet standing index also can be used to compare individual subjects within a group. Another potentially useful way to apply the quiet standing index is to monitor how C' varies for an individual over time. By measuring the quiet standing index of an individual every year or every few years, and computing a trend line, a potentially troublesome *change* in the quiet standing index might be detected. If the measured $C' > 1$ and the trend is sharply upward, then this may indicate the beginning of a reduction in steadiness and an increased risk of falling.

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