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Development of a New Approach to Quantifying Stepping Stability Using Ensemble Empirical Mode Decomposition

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Abstract

Everyday walking is often interrupted by obstacles and changes in the environment that make gait a highly non-stationary process. This study introduces a novel measure, termed the Step Stability Index (SSI), to quantify stepping stability under non-stationary walking conditions among older adults. This index is based on the ensemble empirical mode decomposition method. We hypothesized that a higher SSI would indicate a more stable gait pattern and could be used to assess fall risk. Accelerometer-derived signals (vertical direction) were analyzed from 39 older adults with a history of 2 or more falls in the past year (i.e., fallers) and 42 older adults who reported no falls in the previous year (i.e., controls) under three walking conditions: baseline walk with and without a harness, and obstacle course with a harness. In each condition, the subjects

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wore a small, light-weight sensor (i.e., a 3 dimensional accelerometer) on their lower back. The SSI was significantly higher ($p = 0.05$) in the controls than in the fallers in all three walking conditions. The SSI was significantly ($p < 0.0001$) lower for both the controls and the fallers during obstacle walking compared with baseline walking. This finding is consistent with a less stable step pattern during obstacle negotiation walking. The SSI was correlated with conventional clinical measures of mobility and fall risk (the correlation coefficient, r , ranged from 0.27 to 0.73, $p < 0.05$). These initial findings suggest that SSI, an index based on the ensemble empirical mode decomposition, may be helpful for quantifying gait stability and fall risk during the challenges of everyday walking.

Keywords

accelerometer; aging; algorithms; ensemble empirical mode decomposition; falls; gait; older adults

1. Introduction

Decreased stability of the stepping pattern has been associated with fall risk among older adults [1-3]. A number of metrics have been used to quantify “stepping stability.” These include indices that reflect step-to-step variability [4-6], the harmonic ratio of gait smoothness [7], local dynamic stability [8], and step and stride degrees of regularity, which are based on autocorrelation functions [9-11]. However, the analytical and computational approaches underlying these methods are generally not readily applicable when the gait time series is not stationary. The time series generated by a stationary process has a joint probability distribution that does not change when shifted in time or space. Walking, in contrast, is often interrupted by obstacles and changes in the environment that render the gait pattern into a non-stationary process.

The ensemble empirical mode decomposition (EEMD) technique is a new computational tool that has been applied to the analysis of nonlinear and non-stationary data [12]. We speculated that the EEMD might be helpful in quantifying stepping stability in non-stationary time series derived from walking, since the EEMD method decomposes non-stationary signals into components with different characteristic cycle lengths (or frequency ranges). Specifically, we hypothesized that the energy, as measured by standard deviation, of the component at the step frequency would be higher than the energy of higher frequency components that likely relate to subtle unsteadiness of stepping [13-15]. We applied the EEMD technique to continuous gait signals to develop a Step Stability Index (SSI). The SSI was defined as the ratio of the energy of the dominant component in a fully step cycle to the energy of faster (higher frequency) components. Our assumption, therefore, is that higher Step Stability Index (SSI) values will reflect a more stable gait pattern.

The goal of the present work is to develop a method of quantifying stepping or gait stability among older adults, based on measurements of a single body-fixed sensor, e.g., an accelerometer, worn on the lower back, and to begin to evaluate the algorithm on data collected in the laboratory during usual-walking and while subjects negotiated obstacles, a condition in which interruptions and, therefore, non-stationarities are commonplace.

2. MATERIALS AND METHODS

2.1 Subjects

81 community living older adults were studied. Subjects were included in this study if they were between the ages of 65 to 90 years of age, had no clinically diagnosed gait or balance

disorders, and scored above 24 points on the Mini Mental State Examination. Subjects were classified as fallers and controls based on their self-report of previous falls. If subjects reported two or more falls in the past year, they were considered as fallers; otherwise they were classified as controls [16,17]. This study was approved by the human studies committee of the Tel Aviv Sourasky Medical Center and all subjects provided informed written consent prior to participating in the study.

2.2 Protocol

2.2.1 Clinical Tests—The study participants completed a number of functional performance-based assessments of postural control, mobility and fall risk such as the Dynamic Gait Index (DGI) [18], the Berg Balance Scale (BBS) [19], the Timed Up and Go test (TUG) [20] and the Four Square Step Test FSST) [21]. In addition, the Activities-specific Balance Confidence scale (ABC) [22], a measure related to fear of falling, and the Geriatric Depression Scale (GDS) [23] were administered to help characterize the study cohorts.

2.2.2 Ambulatory Assessment—Subjects walked for one minute under three different conditions: 1) baseline, usual walk; 2) baseline, usual walk with a harness; and 3) an obstacle course walk with a harness, while negotiating obstacles including boxes and other items that required stepping over or walking on an uneven surface. Subjects wore a small, light-weight sensor (DynaPort Hybrid, McRoberts) on a belt on their lower back. The dimensions of the sensor are $87 \times 45 \times 14$ mm; it weighs 74 g. The DynaPort Hybrid includes a triaxial accelerometer (sensor range and resolution are: $\pm 6g$ and $\pm 1mg$ respectively) and a triaxial gyroscope (sensor range and resolution are: ± 100 degrees/sec and ± 0.0069 deg/sec, respectively). The signals were recorded on a Secure Digital (SD) card at a sample frequency of 100 Hz, and later transferred to a personal computer for further analysis using MATLAB, the Mathworks software. Since the vertical acceleration axis has previously been shown to give the most information on the gait cycle [24], one minute of the acceleration signal on this axis was analyzed in this initial study.

2.4 SSI: A new metric for quantifying stepping stability

2.4.1 Ensemble Empirical Mode Decomposition (EEMD)—The EEMD method is a noise-assisted enhancement of the EMD method proposed by Huang *et al.* in 1998 [12, 25]. EMD and EEMD are adaptive decomposition methods based on the local characteristic time scale of the data, which is applicable to nonlinear and non-stationary processes. These decompositions have the advantage of automatically identifying the intrinsic time scales of the data without any assumptions regarding signal stationarity. An example of the EEMD decomposition of a raw acceleration signal is shown in Figure 1; the modes were ordered according to decreasing frequency.

2.4.2 Definition of Step Stability Index (SSI)—Each acceleration signal in the vertical direction was decomposed into a series of intrinsic mode functions (IMFs) using the EEMD method. The number of IMFs depends on the length of the original data. One minute recordings, sampled at 100 Hz, yield time series with 6,000 data points. The EEMD method decomposes signals of this length into 8 IMFs. Based on visual inspection of the dynamic patterns of the original signal and of the IMFs, we inferred that the 4th IMF, denoted as IMF4, captured the dominant oscillatory patterns at step frequency, while IMF1, IMF2 and IMF3 captured the higher frequency fluctuations within each step. Figure 2 shows raw acceleration signals in the vertical direction, recorded under baseline walk and the obstacle negotiation, and the dominant oscillatory and faster modulation components obtained using EEMD. The components were normalized by dividing each component by the standard deviation of the raw signal to minimize the influence of individual subject differences.

As noted, we hypothesized that a “smooth” step should have more “energy” in key components of the step cycle itself and less “energy” within each step. That is, subjects who walk with a more stable gait pattern would have relatively high energy in IMF4 and low energy in IMF1, IMF2 and IMF3. We calculated the standard deviation (SD) to quantify the “energy” of each IMF. The new Step Stability Index (SSI) was defined as:

$$\text{SSI} = (\text{SD of IMF4}) / (\text{SD of IMF1} + \text{SD of IMF2} + \text{SD of IMF3})$$

2.5 Statistical Analysis

Outcome measures were compared between the groups using the Mann Whitney test. Wilcoxon Signed Rank tests were used for intra-group comparisons. Least square models were used to assess the relationships between the SSI and clinical measures. The independent variable was the SSI and the dependent variables were the clinical measures. The *r* and *p* values presented were adjusted for age and gender. Group results are summarized as mean $\pm$ SD or as indicated. A *p*-value ≤ 0.05 was considered significant.

3. Results

3.1 Subject Characteristics

Based on fall history, 39 subjects were classified as fallers and 42 subjects as controls. The mean age and gender distribution were similar in the two groups. Table 1 presents the values of the clinical variables and of the new SSI for the fallers and controls. The differences between the two groups were statistically significant for all variables but age and gender and are consistent with the fact that controls have better balance and a more stable gait.

3.2 Intra-group SSI differences from baseline walking to obstacle walking

To test the hypothesis that higher SSI values reflect a more stable gait pattern, the step patterns of each subject were compared under two different conditions: baseline walking with a harness and during an obstacle walk with a harness. A harness was used to ensure that no falls occurred. The “walk with harness” was selected as the reference because no significant differences were observed when comparing baseline walks with or without a harness. The comparable condition of wearing a harness for both the baseline and obstacle walks isolated the effect of the obstacles.

As shown in Figure 3, 27 controls (Fig. 3A) and 27 fallers (Fig. 3B) performed both the baseline walk and the obstacle walk with a harness. The SSI was lower during the obstacle negotiation condition, compared to baseline walking, in 26 out of 27 control subjects (Fig. 3A, Wilcoxon Signed Rank test, $p < 0.0001$). Similarly, the SSI was lower in 25 out of 27 fallers during obstacle walking (Fig. 3B, Wilcoxon Signed Rank test, $p < 0.0001$). Both of these results are consistent with a less stable stepping pattern during obstacle negotiation walking. Only one control subject and two fallers slightly increased their SSI during the obstacle cross walk.

3.3 Inter-group SSI differences in three walking conditions

To examine if this new SSI is related to fall risk, as reflected by a history of falls, the SSI of the control subjects and the fallers was compared under the three walking conditions. The inter-group comparisons are shown in Figure 3C. The SSI index was higher in the control group than in the fallers in all three walking conditions. The group differences were significant during baseline walking without the harness ($p = 0.006$), baseline walking with the harness ($p = 0.003$) and obstacle walking ($p = 0.05$).

3.4 Relationships between SSI and other clinical measures

The new SSI measure proposed in this study was linearly correlated with conventional clinical measures of mobility and fall risk (see Table 2). We examined the correlations between the clinical measures and the SSI and normalized IMF1~IMF4 for all subjects, as well as for the controls and fallers, separately. The SSI was positively associated with Berg Balance Score, Dynamic Gait Index and gait speed. Different relationships were observed for the Timed Up and Go and the Four Square Step test. The SSI was negatively correlated with Timed Up and Go and Four Square Step Test (where lower values reflect better performance). These findings also indicate that better performance was associated with higher SSI values. For the IMFs, similar relationships were noted between IMF1~IMF3 and the conventional clinical measures. In contrast, IMF4 had the opposite relationship as that of IMF1~IMF3. For example, IMF2 and IMF3 were positively associated with Timed Up and Go, while IMF4 was negatively associated with Timed Up and Go. IMF1 and IMF3 were negatively associated with Dynamic Gait Index and Gait speed, while IMF4 was positively associated with the Dynamic Gait Index and gait speed. IMF3 was negatively associated with the Berg Balance Score, while IMF4 was positively associated with the Berg Balance Score. IMF2 was positively associated with Four Square Step Test, while IMF4 was negatively associated with Four Square Step Test scores.

4. Discussion

The goal of this study was to develop a measure for quantifying walking stability in the presence of non-stationarities in gait signals. To this end, we developed a Step Stability Index, SSI. Our preliminary findings suggest that this new metric is a potentially useful measure of stepping stability. The SSI significantly decreased when subjects walked while negotiating obstacles, indicating that it is sensitive to environments that disrupt the normal gait pattern. The SSI was also significantly lower in fallers compared to controls in all three walking conditions tested. Finally, the SSI was significantly correlated with traditional performance-based measures of functional performance and fall risk.

The SSI has several potential advantages over other approaches that have been used to quantify gait stability. Existing methods that reflect regularity or smoothness in gait are generally based on spectral analyses via the fast Fourier transform (FFT) [26] or the closely related autocorrelation function [9-11]. However, when the time series are not stationary, as in the case of everyday walking or, especially, during obstacle negotiation, the assumptions that underlie these methods are no longer valid [25]. Moreover, when applying the Fourier transform to define the ratio between the dominant frequency “energy” and “energy” of the higher frequencies within each step, a fixed threshold or cut-off point must be determined. When we attempted to do this, we could not find a consistent range for the dominant frequency for each subject, and the dominant frequency within each step appeared to fluctuate with gait speed even for the same subject (data not shown). Thus, using traditional spectral analyses and related techniques, it is difficult to define a consistent threshold to distinguish relatively low frequencies and high frequencies. To apply an approach based on the FFT, a sophisticated procedure would be necessary to locate the threshold for the cut point between the low and high frequency for each subject’s walk, something that was beyond the scope of this study. In contrast, the EEMD, and hence the SSI, is based on a self-adaptive method, where the data itself dictates the boundaries and the signal is decomposed to automatically obtain the low frequency and high frequency modes without any a priori assumptions.

Other potential advantages of the SSI include its relative computational simplicity and the fact that it is self-adaptive. Furthermore, the ability to investigate the separate intrinsic mode functions (IMFs) in addition to the SSI may enable researchers to explore specific

impairments in certain intrinsic scales of the gait patterns and their relationship to different pathologies and interventions. The observed relationships between the clinical measures and the intrinsic mode functions support the definition of the SSI, which is based on the hypothesis that a “smooth/stable” gait pattern should have more “energy” within the dominant oscillatory component at the step frequency (IMF4), and less “energy” on faster modulation components (IMF1~IMF3). Further, they illustrate the distinct properties of the different modes and their association with clinical outcomes.

Researchers have long commented on the need for including additional constructs of locomotion in gait analysis [27, 28]. The present work can be expanded upon in several different ways to address these needs. The scope of our work focused on the vertical acceleration axis. Examination of other acceleration and angular velocity axes may provide additional insight into balance control mechanisms and perhaps improve clinical utility. Further, since the empirical mode decomposition algorithm is a powerful method that can be applied to nonlinear and non-stationary data, we envision using this method in the context of real-life, daily living continuous recordings of accelerometer data. The importance of assessing fall risk in the home environment, during “community ambulation” [29] is becoming increasingly recognized. Using the newly proposed method in real-life settings may lead to a sensitive, objective marker of fall risk that augments previously proposed methods for quantifying gait in complex, daily-living settings using a single body-fixed sensor [30]. The result of the present study sets the stage for these future directions.

The present study has several limitations: 1) we did not statistically adjust for multiple comparisons. However, the fact that many of the observed differences were quite robust, suggests that the findings would have persisted in the presence of such adjustments; 2) in the present study, we used one minute of data. Whether the SSI depends on the length of the time series will require future studies; 3) for all subjects in this study, IMF4 captured the oscillatory patterns at the step frequency, despite significant differences in walking speed and unique step patterns. However, if a person walks in a highly pathologic way, the step oscillatory pattern may not appear in IMF4 and may require visual selection of the appropriate IMF; and 4) while the utility of this new approach was supported by the results obtained during three different conditions, a prospective study in a larger sample will be needed to assess the ability of the SSI to predict future falls. A prospective study will also allow us to determine if the SSI is a more accurate and more sensitive measure of fall risk, compared to other approaches, and whether this method could be used in combination with existing metrics to improve prediction.

In conclusion, our results suggest that an approach that combines an accelerometer with an algorithm based on the empirical mode decomposition algorithm may be utilized for evaluating stepping stability and fall risk among older adults. These findings support the idea that the SSI can be used to quantify gait dynamics and discriminates between elderly subjects with and without a history of falls. Nonetheless, additional work needs to be carried out to assess the predictive value of the SSI and to determine its sensitivity to various pathologies and interventions.

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Highlights

We propose a Step Stability Index (SSI) for quantifying non-stationary gait.

The SSI was higher in controls than in fallers in 3 walking conditions ($p < 0.05$).

The SSI was lower during obstacle walking ($p < 0.001$) than in normal walking.

The SSI was correlated with conventional measures of mobility and fall risk.

Initial findings suggest that the SSI can assess walking in a complex environment.

Figure 1.

Example of a segment of an acceleration signal in the vertical direction (baseline walking) from a control subject along with the intrinsic mode functions (IMF 1 to 8) derived using the EEMD method. The IMFs were ordered according to decreasing frequency content.

Figure 2.

Acceleration signals in the vertical direction for baseline and obstacle walking for a control subject and a faller, along with the selected IMFs obtained using the EEMD method. The two subjects shown here were randomly selected. The number of steps in each plot is approximately 20. IMF4 captures the oscillatory patterns at step frequency. IMF1+IMF2+IMF3 captures oscillatory patterns at frequencies higher than the step frequency. The dashed-line rectangle in plots (B) and (D) highlight regions where obstacles were being negotiated. Of note, we analyzed one-minute signals but for clarity only display 10 sec segments.

Figure 3.

SSI values for controls and fallers during baseline walk and obstacle cross walk. Plots (A) and (B) show the SSI values for individual subjects and plot (C) shows summary statistics. The height of the bars and the error bars represent mean and standard error of the mean values, respectively. Of note, SSI was higher for baseline than obstacle walking in 26 out of 27 controls and in 25 out of 27 fallers.

Table 1

Group differences of the clinical measures and the new SSI measure.

	Controls	Fallers	<i>p-value</i>
Age (years)	78.83 ± 4.64	77.92 ± 5.00	0.63
Gender (% female)	61.9%	59.0%	0.61
Activities-specific Balance Confidence scale (max. score 100.0)	84.19 ± 16.08	72.62 ± 15.72	0.002
Geriatric Depression Scale (max. score 15)	2.26 ± 2.28	4.33 ± 3.00	0.002
Berg Balance Score (max. score 56)	53.31 ± 2.63	50.82 ± 4.96	0.05
Dynamic Gait Index (max. score 24)	22.29 ± 1.80	20.31 ± 3.68	0.04
Timed Up and Go (sec)	10.11 ± 2.53	12.41 ± 5.90	0.03
Four Square Step Test (sec)	11.90 ± 3.17	15.45 ± 7.07	0.04
Baseline Gait speed (m/sec)	1.19 ± 0.24	1.00 ± 0.28	0.01
SSI (baseline walk no harness)	0.86 ± 0.26	0.68 ± 0.26	0.006
SSI (baseline walk with harness)	0.83 ± 0.23	0.65 ± 0.23	0.003
SSI (obstacle negotiation walk)	0.55 ± 0.16	0.47 ± 0.16	0.05

Results are presented as mean ± standard deviation (SD); *p*-values were obtained using the Mann Whitney test. For the Step Stability Index, SSI, higher scores are indicative of better performance. For the Berg Balance Scale, the Dynamic Gait Index and the Activities-specific Balance Confidence Scale, higher scores reflect better balance, gait and confidence, respectively. Scores further away from 0 reflect more symptoms on the Geriatric Depression Scale.

Table 2

Correlations between the new SSI, the intrinsic mode functions (IMFs), and the clinical measures

		SSI	IMF1	IMF2	IMF3	IMF4
		<i>r (p-value)</i>	<i>r (p-value)</i>	<i>r (p-value)</i>	<i>r (p-value)</i>	<i>r (p-value)</i>
Gait Speed	All subjects	<i>0.49 (0.003)</i>	0.45 (0.03)	NS	NS	<i>0.40 (0.004)</i>
	Controls	NS	NS	NS	NS	NS
	Fallers	<i>0.73 (0.008)</i>	NS	NS	0.72 (0.009)	<i>0.68 (0.02)</i>
Berg Balance Scale	All subjects	<i>0.44 (0.006)</i>	NS	NS	0.42 (0.02)	<i>0.40 (0.0004)</i>
	Controls	NS	NS	NS	NS	NS
	Fallers	<i>0.60 (0.001)</i>	NS	NS	0.70	<i>0.22 (0.0001)</i>
Dynamic Gait Index	All subjects	<i>0.55 (0.0002)</i>	NS	NS	0.54 (0.0008)	<i>0.45 (<0.0001)</i>
	Controls	NS	0.41 (0.03)	NS	NS	NS
	Fallers	<i>0.62 (0.004)</i>	NS	NS	0.72 (<0.0001)	<i>0.39 (0.0006)</i>
Timed Up and Go	All subjects	0.41 (0.003)	NS	NS	NS	0.20 (0.001)
	Controls	NS	<i>0.46 (0.007)</i>	<i>0.43 (0.04)</i>	NS	NS
	Fallers	0.27 (0.05)	NS	NS	<i>0.30 (0.03)</i>	NS
Four Square Step Test	All subjects	0.51 (0.02)	NS	NS	NS	0.44 (0.003)
	Controls	NS	NS	NS	NS	NS
	Fallers	0.58 (0.04)	NS	<i>0.54 (0.04)</i>	NS	0.34 (0.04)

All the correlations are presented as *r* and *p*-values. The values in bold and italic indicate positive correlation, other values indicate negative correlation. NS represent no significant correlation. All correlations are adjusted for age and gender.