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Metrics from in-home sensor data to assess gait change due to weighted vest therapy☆

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ABSTRACT

A set of metrics and a methodology were developed to characterize a subject's ability to ambulate. These metrics use the movement of the subject's centroid as detected by an inexpensive depth camera system. The centroid is chosen as it is less sensitive to cluttered environments typically found in a person's home. Three classes of metrics focusing on three major categories of motion were developed. The first class measures fundamental characteristics of movement in three directions. The second class focuses on measuring the walk's entropy. The third class uses periodicity in the subject's motion to deduce temporal gait parameters including stride length. Metrics are validated and compared to existing Fall Risk Assessments (FRA's). While results show strong correlation to many FRA's, not every subject has the same relationships between metrics and FRA's suggesting a unique "fingerprint" of metrics associated with a subject and/or their condition.

The methodology was tested using a group of subjects undergoing Balance Wear Therapy targeting sensory inputs to improve balance control. The ability of the metrics to detect changes in the subject's ambulation when the vest is either put on, or taken off was also explored. Results show sufficient sensitivity to detect changes when the vest is donned and doffed. Many effects are not seen immediately, but over 2–4 h following donning or doffing the vest. Results also demonstrate the ability, using the size of the analysis window, to focus on the time required for the effects of each metric to change.

1. Introduction

More than one third of older adults fall each year (Kannus et al., 1999; Lord, Ward, Williams, & Anstey, 1993; Sattin et al., 1990; Scuffham, Chaplin, & Legood, 2003). Of these falls, 10% to 20% cause moderate to severe injuries. Of these falls, about three percent will result in a fracture of some kind (Nevitt, Cummings, Kidd & Black, 1989). According to the United States Centers for Disease Control and Prevention, in 2012, the direct medical cost of falls among older adults, adjusted for inflation, was over $30 billion (Costs of Falls Among Older Adults | Home and Recreational Safety | CDC Injury Center, n.d.).

Beyond the physical and immediate financial cost of falls, there are longer term costs, psychological, physical and financial, that

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result from falling. Howland reported that the fear of falling may, in fact, affect social interaction regardless of actual fall risk (Howland et al., 1993). Nevitt found that approximately one quarter of falls cause the subject to limit their normal activities, usually because of injury, but often simply due to the fear of falling again (Nevitt et al., 1989). Reducing the occurrence of falls, then, can go a long way in reducing the direct and indirect costs of falls. Not only will the patient's life be extended, and direct hospitalization costs be reduced, but more patients will be able to maintain their functional independence longer, delaying or eliminating their dependency on family, friends, or the healthcare system as a whole. This will lead to a higher quality of life.

To better monitor the population of older adults in order to identify the potential of falling before it happens or between exams, a set of metrics was developed that can be used to study the effects of therapies and monitor a subject's gait as the subject carries out their typical day to day activities. Since the target is the home environment, we focused on using inexpensive depth cameras, such as the Microsoft Kinect®.

In order to test these algorithms and metrics, we chose to use BalanceWear Therapy. BalanceWear Therapy (BWT) consists of strategically placing sensory inputs (small ¼ to ½ pound weights) at various locations on the trunk. BWT is currently being utilized to treat patients with Multiple Sclerosis, Parkinson's disease, traumatic brain injury, vestibular issues, and ataxia. The BalanceWear® vest, produced by Motion Therapeutics in Oxnard, CA, consists of a vest, worn on the torso with Velcro areas where small, light weights are attached to the inside of the vest. The physical therapist performed a BalanceWear assessment to identify directional imbalance of a subject and strategically placed ¼ to ½ pound increments of weight in specific locations on the vest to improve directional balance and postural control. The patient was then instructed to wear the vest for several hours once or twice during the day. Studies conducted have focused on the clinical effects of the vest (Gibson-Horn, 2008; Widener, Allen, & Gibson-Horn, 2009a, 2009b) but have not investigated how the vest specifically impacts the patient's ambulation beyond gait speed.

A brief discussion of background and related work is included in Section 2. The Methods section describes how the data were collected and analyzed. The Metrics section discusses how each metric is computed. The Results and Discussion sections highlight the findings.

2. Related work

2.1. Fall risk assessments

2.1.1. Timed Up-and-Go

The "Timed Up and Go" (TUG) test is a modification of the "Get Up and Go" test developed by Mathias et al. (1986) to add a temporal component to the assessment (Podsiadlo & Richardson, 1991). Their research has shown that the TUG test is reliable, correlates well with the Berg Balance Scale, Gait Speed, and Barthel Index of "Activity of Daily Living", and appears to predict the patient's ability to go outside alone safely (Podsiadlo & Richardson, 1991). Other researchers have arrived at similar conclusions (Kristensen, Ekdahl, Kehlet, & Bandholm, 2010; Steffen, Hacker, & Mollinger, 2002).

The TUG is a timed test requiring the subject to rise from a chair, walk 3 m, turn around, return to the chair, and sit back down. Morris, Morris, and Iansek (2001) investigated the reliability of this measure in people with Parkinson's disease. The TUG has been studied with other pathological conditions as well, including amyotrophic lateral sclerosis (Montes et al., 2007), post stroke (Walker, Brouwer, & Culham, 2000), and orthopedic disturbances (Arnold & Faulkner, 2007; Kristensen, Foss, & Kehlet, 2009).

2.1.2. Habitual gait speed

Habitual gait speed (HGS) has been studied as a means to detect a significant change in a person's gait (Bohannon, 1997; Kuo, Leveille, Yu, & Milberg, 2006; Li et al., 2012) which is a predictor of falls. To measure, the subject is asked to walk at a comfortable, habitual speed for a specified distance (20 feet is typical). The walk is timed and the average speed is computed. Bohannon found gait speed to be highly reliable (Bohannon, 1997). This FRA was also shown to be moderately correlated with the subject's age (-0.558; $p < 0.001$), and minimally correlated with height and several mechanical aspects of gait (ankle dorsiflexion strength, hip flexion strength, and hip abduction strength). Knee extension strength was found to be strongly correlated with HGS. Bohannon also published height normalized means and standard deviations for Habitual Gait Speed and Maximum Gait Speed (Bohannon, 1997).

2.1.3. Functional reach

A third common fall risk instrument is the Functional Reach Assessment. This test guides the patient through a series of reach tasks designed to gauge not only the flexibility, but also the ability of the patient to balance sufficiently to reach. This instrument was published in 1990 by Duncan, Weiner, Chandler, and Studenski (1990). The instrument measures the difference between the arm's length and the maximum forward reach using a fixed base of support.

2.1.4. Berg Balance Scale

The Berg Balance Scale (BBS) is a test of 14 different items and is used to monitor fall risk principally relying on assessment of the patient's balance. The 14 activities that comprise the instrument evaluate the subject's balance, ability to rise from and sit on a chair, walking, turning, and balance while walking. In this instrument, all 14 items are rated on a scale of 0 to 4 corresponding from no ability to full ability. The final score is simply the total of each rating out of a total of 56 with each item being equally weighted (Berg, 1989).

2.1.5. Short Physical Performance Battery

The Short Physical Performance Battery (SPPB) test (Guralnik, Ferrucci, Simonsick, Salive, & Wallace, 1995) is commonly used to assess lower extremity strength and has been shown to have some correlation to recurrent falls (Veronese et al., 2014). The instrument measures five aspects of physical performance and scores each in the range of [0..4] where a score of 0 represents the inability to complete the task and a score of 4 indicates the highest level of performance (Guralnik et al., 1995).

2.1.6. Single leg stance

The single leg stance (SLS) assesses fall risk by examining the subject's balance. In this instrument, the subject is asked to stand on one foot with the second foot raised slightly (near the ankle of the stance foot). The time the subject is able to maintain balance is recorded. This is done three times with eyes open and three times with eyes closed. The six trials alternate between eyes opened and closed and a 5 min. rest period was allowed between each pair of trials. Shorter stance times suggest a higher risk of falling (Springer, Marin, Cyhan, Roberts, & Gill, 2007).

2.2. Studies with strategically weighted vest

While there is published research being conducted on the use of strategically weighted vests in other applications, there has been little research on the usefulness of these vests for improving the ambulation and reducing the risk of falls in the elderly. In Gibson-Horn (2008), Gibson-Horn presents the case of a single patient who experienced improved balance and gait during static and dynamic activities. In Widener et al. (2009a), Widener et al. expand upon the previous study to include 16 subjects with Multiple Sclerosis and found significant improvement in several clinical assessments of balance. The last study (Widener et al., 2009a) was a full clinical trial demonstrating immediate improvement of gait velocity and functional activity. Hunt et al. used a force plate in an attempt to deduce how balance is affected by BBTW (Hunt, Widener, & Allen, 2014). More recently, a study (Wallace, Abbott, Gibson-Horn, & Skubic, 2013) has demonstrated the ability to measure changes in some metrics in the home environment. This paper more fully develops these proposed metrics and presents new metrics to serve as a basis to study the mechanisms by which the vest and other interventions improve a subject's ambulation.

2.3. Wearable sensor

Several techniques have been utilized to measure gait parameters in a laboratory or clinical setting. These may rely on markers worn by the subject that are detected by some form of sensor external to the patient or by some form of sensor (usually an accelerometer) worn by the subject. The Vicon® Motion Capture System is an example of the first type. This system requires multiple infrared reflecting markers to be worn by the subject, typically at the joints, in order to capture a skeletal model. Using several infrared emitters and sensors, the position of each of the markers is captured and tracked while the subject is asked to perform various tasks.

While this system is extremely accurate in monitoring the subject's position and works well in a laboratory or clinical environment, it is prohibitively expensive and invasive to use for home monitoring as it requires multiple infrared cameras and emitters to be installed in the subject's environment. Additionally, the markers must be worn at all times for monitoring to occur.

An alternative, and less expensive, solution is achieved using sensors worn by the subject. This common approach (Bamberg, Benbasat, Scarborough, Krebs, & Paradiso, 2008; Boissy, Choquette, Hamel, & Noury, 2007; Giansanti, Maccioni, Cesinaro, Benvenuti, & Macellari, 2008; Marschollek et al., 2008) requires the subject to wear one or more sensors which wirelessly transmits the subject's acceleration in each of three directions, or other related parameters, to a computer which can then deduce location and speed. While the accuracy of this technology is lower than with the Vicon® system, this type of system has been used to determine ambulation parameters. These systems tend to be much more affordable as the sensors are inexpensive and the computational power required to process these data is not great. New sensors are also emerging which are incorporated into clothing or footwear, which may be less obtrusive (Lin, Aosen, Yan, Tomita, & Wenyao, 2016).

The drawback of this type of system is the necessity of wearing a sensor and, typically, recharging the device. For a subject to reliably wear the sensor, it must be designed to be put on, taken off, recharged, and activated easily. The subject must also be wearing the sensor when they are moving throughout their environment. If the subject were to wake in the middle of the night, they may not take the time to put on the sensor, leaving them unmonitored during a period when they are at a higher risk of falling. Studies also show that many seniors refuse to wear wearable sensors or are unable to operate them (Demiris et al., 2004, 2006). Lastly, there are psychological reasons why these wearable sensors may not be accepted by the elderly population which can range from simply being unwilling to wear the device, questioning the need for the device, or even associating the device with an admission of vulnerability (Porter, 2005).

2.4. Non-wearable sensors

What is more practical for today's vulnerable seniors, particularly for continuous in-home monitoring, is an inexpensive system that does not require any direct interaction by the user. Several approaches have been used including single camera (Courtney & de Paor, 2010), multiple orthogonal webcams (Wang et al., 2013; Wang, Skubic, Abbott, & Keller, 2011), (Chavez-Romero, Cardenas, Rendon-Mancha, Vernaza, & Piovesan, 2015), and Doppler radar to monitor subject movement and or falls (Wang, Skubic, Rantz, & Cuddihy, 2014). An inexpensive depth camera, such as the Microsoft Kinect system, has been used to measure gait parameters. This approach uses the movement of the subject's feet to measure stride length, stride time and walking speed (E. Stone & Skubic, 2011; E.E. Stone & Skubic, 2013; E. Stone, Skubic, Rantz, Abbott, & Miller, 2015; Chang, Chen, & Huang, 2011; Dutta, 2012; Clark, Pua, Bryant, & Hunt, 2013; Angad, Shandilya, & Kumar, 2015). While this system generates good results as compared to ground truth generated by a Vicon® Motion Capture System, it suffers when the subject's feet are occluded by objects in the subject's environment (tables, chairs, etc.…). In this paper, we investigate a set of metrics that can be computed using centroid values extracted from depth images taken by an inexpensive depth camera system. The remainder of this paper describes the development, validation, and use of such metrics.

3. Methods

3.1. Centroid measurement

One solution to the problem of occluded legs and feet is to monitor the centroid of the subject's image. As a person ambulates, there is oscillation in the vertical direction when the heel plant is made at the start of a new step to the maximum when the opposite leg is in the middle of its swing. Similarly, there is oscillation in the lateral direction as the subject's center of mass shifts over the planted foot to balance the subject when the swinging foot is lifted. Since the subject's centroid is easier to identify and less likely to be occluded, we hypothesize this would improve the ability to measure in an unstructured and cluttered environment.

3.2. Data collection

After receiving approval from the University of Missouri Institutional Review Board, a Microsoft Kinect system was placed in the apartments of four subjects. Subjects were chosen based upon their current physical condition and likely benefit of the BBTW strategically weighted BalanceWear Therapy. Depth image data are used directly as in previous work (Stone & Skubic, 2011; Stone & Skubic, 2012). The system collected and stored the centroid location at 8 to 30 frames per second for each object that moved throughout the room.

The camera system was active 24 h per day in the living room of each apartment, and any walks made by the home resident or any visitors during that time were captured. Data were captured for roughly 220 to more than 500 days, depending upon the subject. Walks by people other than the subject are classified as visitors and culled as described in the next section.

3.3. Data analysis

The Kinect system was used to collect the raw depth image data, and the dynamically updated background was removed. The foreground image was segmented, and a 3-D point cloud was generated, representing the person moving about the scene. The centroid values were computed from this point cloud (E. Stone & Skubic, 2011). Since the data were collected in a subject's unstructured and cluttered apartment, and not a laboratory setting, the walks were furthered filtered by culling all walks that were not considered purposeful. Purposeful walks are defined as walks at least 1.22 m long, speed at least 12.7 cm/s, with a duration of at least 1 s (E. E. Stone & Skubic, 2012).

For this study, the centroid data were adjusted to a constant rate of 15 frames per second (averaging multiple points and interpolating missing points). The data were then transformed from a room oriented location (x, y, z) to a triplet of error values (δ_x, δ_y, and δ_z) corresponding to the deviation from the expected location (x', y', z') along the walking path. The expected location was found by projecting a best-fit line over one second of data, centered on the current point in time, and extending it to the next frame. By convention, the X direction was chosen to be in the direction of travel, the Y direction was lateral, and the Z direction was vertical. The positive directions for X, Y, and Z indicate forward, left, and up, respectively. This process is illustrated in Fig. 1.

The last pre-processing step removes those samples that are not likely to be generated by the subject. To do this, a Gaussian mixture model (GMM) clustering algorithm was applied using height and speed as features. The GMM is initialized randomly and 50 models are computed for N + 1 clusters where N represents the number of residents in the apartment. The Fowlkes-Mallows score is computed for each model and the model with the best score is selected as the winner. The data in the smallest cluster is discarded as belonging to visitors. Lastly, for apartments with two residents, the cluster for each resident is differentiated using their respective heights. This is similar to the approach used in E. E. Stone and Skubic (2013).

4. Metrics

4.1. Basic metrics

After pre-processing, the following metrics are computed using the error values generated[1].

- Asymmetry is computed in all three directions as the ratio between the mean error ($\overline{\delta_i}$) and the maximum error (δ_i) for a given walk (i = x, y, or z). This measures the degree to which the walk favors one side versus the other.

[1] A table listing the variable names and meanings for this article is provided in Appendix A.

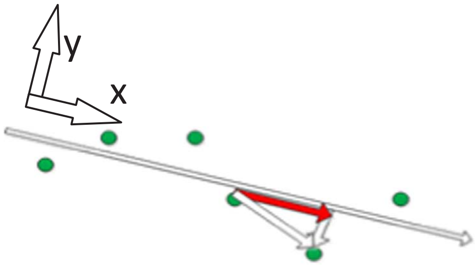

Fig. 1. Diagram of the process used to generate the (δ_x, δ_y, *and* δ_z) error signals from the room coordinates (x, y, z). The X-Y plane is shown (as if looking down from the ceiling). The dots represent the measured position. The long arrow represents the 1 s average path centered on the current position. The red (dark) arrow represents the expected position at the next sample. The error in the X direction is simply the difference between the expected position and the component of the actual displacement. The shortest arrow represents the error in the Y direction and is the component of the error along a line perpendicular to the expected path. The error in the Z direction is simply the difference between the z component of the centroid and the average centroid height. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

$$A_i = \frac{\overline{\delta_i}}{MAX(|\delta_i|)} \tag{1}$$

- Peak-to-Peak (p2p) is computed in all three directions as the difference between the largest error values in both the positive and negative directions.

$$p2p_i = MAX(\delta_i) - MIN(\delta_i) \tag{2}$$

- Walk speed is computed by dividing the distance covered by the duration of the walk (T). The variable n represents the number of samples for the walk.

$$s = \frac{\sum_{i=1}^{n-1} \sqrt{(x'_{i+1} - x'_i)^2 + (y'_{i+1} - y'_i)^2}}{T} \tag{3}$$

- The ten foot walk metric is computed utilizing the total actual distance moved by the centroid (D) and the duration of the walk(T).

$$W = T \times \frac{10 \quad ft.}{D} \tag{4}$$

- Walk Efficiency is computed as the ratio between the most direct walking path (x', y') and the actual path (x, y) using the following formula:

$$E = \frac{\sum_{i=1}^{n-1} (\sqrt{(x'_{i+1} - x'_i)^2 + ((y'_{i+1} - y'_i)^2}}{\sum_{i=1}^{n-1} (\sqrt{(x_{i+1} - x_i)^2 + ((y_{i+1} - y_i)^2}} \tag{5}$$

4.2. Entropy metrics

Entropy measures the uncertainty, irregularity, or randomness in a given signal. In this case, entropy will be used to measure the irregularity in the subject's gait. The hypothesis is that a healthy individual's gait is characterized by more regular, sinusoidal, movement laterally and vertically. As a subject's gait degrades due to age or disease, the gait can become more irregular. This would cause entropy measurements to increase as the subject's gait degrades indicating a higher risk of falling. Arafat *et al.* used entropy to study gait deficiencies and identify ataxia in horses (Arafat & Skubic, 2003). In his work, he utilized three different computations of entropy. The first, Eq. (6), by Deluca and Termini (1972), is given by:

$$H_{DTE}^{\delta_k} = -K \sum_j \delta_{kj} log_2 \delta_{kj} + (1-\delta_{kj}) log_2 (1-\delta_{kj}) \tag{6}$$

Eq. (7), developed by N. R. Pal and Pal (1989) is given here:

$$H_{PPE}^{\delta_k} = K \sum_j \delta_{kj} e^{1-\delta_{kj}} + (1-\delta_{kj}) e^{\delta_{kj}} \tag{7}$$

And Eq. (8), developed by Pal and Bezdek (1994):

$$H^{\delta_k}_{\alpha QE} = K\sum_j \delta^{\alpha}_{kj} + (1-\delta^{\alpha}_{kj})^{\alpha} \tag{8}$$

In all three formulae, δ_{kj} is the error signal in a particular direction. K is a normalization constant taken to be 1 in each of these measurements.

The entropy metrics determine the randomness or unpredictability of the subject's walks. In a healthy younger person, examining the movement of their centroid in the Y direction (lateral to the direction of motion) would show a fairly regular sinusoid as the centroid moves back and forth to keep the subject's center of mass above the planted foot. For a subject with difficulty balancing, as an example, there may be some additional random movement due to unsteadiness. It is this extra randomness that this metric will measure. For a regular, more sinusoidal-like signal, the entropy will be low. For a more irregular, random centroid path, the entropy will increase.

4.3. Temporal metrics

This estimation exploits the periodic nature of the error value δ_z during a typical walk. During a normal stride, the centroid reaches a vertical minimum value when both feet are in contact with the ground and reaches a maximum when either foot is in the middle of its swing and closest to the other leg. By measuring the period of this oscillation, the average stride time for a particular walk can be deduced.

The first step is to separate the components of centroid movement that most strongly captures the periodic components of a walk. In particular, we want to focus on the sudden change in vertical acceleration and velocity coincident with the foot plant. To isolate this, the vertical centroid signal is filtered using a 5 Hz high pass digital filter to remove low frequency components. The signal is then passed through a three point triangular filter shown here:

$$\delta_z^{'}(i) = \frac{\delta_z(i-1) + 2\delta_z(i) + \delta_z(i+1)}{4} \tag{9}$$

During development, it was found that for steps that do not include crisp foot plants, the accuracy of the algorithm decreases. While the lateral component of a typical healthy walk should resemble a sinusoid, the vertical component should more closely resemble a sequence of arches, more like |sin(x)| than sin(x). To isolate these walks, the Deluca and Termini entropy equation (Eq. (6)) was used to compute the entropy of the vertical component of the centroid movement. Through experimentation, it was found that if walks do not score an entropy value in the range of [1..10], they will generate a large amount of error in the stride time value. Consequently, these walks with an entropy value outside of this range are discarded.

Lastly, a Fast Fourier Transform (FFT) is taken of the filtered signal. The period corresponding to the highest peak that is greater than zero is selected. Stride time is defined as the average time between the same events (for example, right foot heel strike) in two successive strides. Stride time, then, is computed by doubling the average step time (reciprocal of the dominant frequency in the FFT).

Once stride time is computed, the left and right steps are isolated using the following algorithm:

1. Compute the vector, **M**, containing the time indices of all of the local minima in the δ_z signal.
2. Compute the vector, **P**, containing the time indices of all of the local maxima in the δ_z signal.
3. Compute Step Time on both sides of the walk:

$$ST1 = \frac{1}{n/2}\sum_{i=ODD}^{n-1} \boldsymbol{M}(i+1) - \boldsymbol{M}(i) \tag{10}$$

$$ST2 = \frac{1}{n/2}\sum_{i=EVEN}^{n-1} \boldsymbol{M}(i+1) - \boldsymbol{M}(i) \tag{11}$$

4. Compute Left Step Time and Right Step Time
   a. If $(\delta_y(\frac{\boldsymbol{M}(2)-\boldsymbol{M}(1)}{2}) > 0)$
      i. Left Step Time = ST1
      ii. Right Step Time = ST2
   b. else
      i. Left Step Time = ST2
      ii. Right Step Time = ST1

Bounce is then computed using the following formula:

$$B = MEAN(\delta_z(\boldsymbol{P})) - MEAN(\delta_z(\boldsymbol{M})) \tag{12}$$

Trunk sway is computed by applying steps 1, 2 on the δ_y signal then computing trunk sway using Eq. (13).

$$S = MEAN(\delta_y(\boldsymbol{P})) - MEAN(\delta_y(\boldsymbol{M})) \tag{13}$$

4.4. Minimum detectable change

One use for these metrics is to study specific therapies to determine if there are any immediate or short term effects of a particular therapy. For example, one might want to study how putting on a set of shoe lifts impacts gait and ambulation. The clinician may want to monitor the subject as he goes about his daily activities without the lifts, then have him put the lifts on for a couple hours during the day. These proposed metrics could be used to study the effects on gait of the lifts, but some mechanism is needed to determine if the changes seen are statistically significant. Because the units for the proposed metrics vary, as does the number of walks for each particular subject, the concept of Minimum Detectable Change (MDC) was used. This value is computed from the standard deviations of the metrics both pre- and post-event. If the metric's value following the event deviates from the pre-event value by more than the MDC, we consider the change significant. MDC is computed using the approach defined in Spooner (2011). This calculation is skipped for pre-event distributions that are not Gaussian or if the pre-event signal is strongly correlated with the post-event signal ($\rho > 0.50$).

The computation is a two-step process using the following formulae. The first step is to compute the statistical “t” value using the following:

$$t = \frac{\overline{X}_{pre} - \overline{X}_{post}}{S_{X_{pre}X_{post}}\sqrt{\frac{1}{n_{pre}} + \frac{1}{n_{post}}}} \tag{14}$$

where

$$S_{X_{pre}X_{post}} = \sqrt{\frac{(n_{pre}-1)S^2_{X_{pre}} + (n_{post}-1)S^2_{X_{post}}}{n_{pre} + n_{post}-2}} \tag{15}$$

and $\overline{X}_{pre}$ and $\overline{X}_{post}$ are the means for the pre-event distribution and the post-event distribution respectively. n_{pre} and n_{post} are the number of samples in the pre- and post-event distributions. $S^2_{X_{pre}}$and $S^2_{X_{post}}$are the variances for each distribution. Finally, MDC is computed using the following formula:

$$MDC = t\sqrt{\frac{MSE}{n_{pre}} + \frac{MSE}{n_{post}}} \tag{16}$$

where MSE is the pooled mean squared error which is estimated by the variance for the pre-event distribution.

4.5. Pearson Correlation

Pearson’s Correlation was used to characterize the relationship between the behavior of the metrics and Fall Risk Assessment data. It measures the tendency for two variables to co-vary and has a range of $|\rho| = [0..1]$. A correlation value of 1 indicates perfect correlation between the two variables – as one changes, the other changes in the same direction. A correlation value of -1 indicates perfect negative correlation – as one changes, the other changes in the opposite direction. The formula for Pearson Correlation between two signals, s1 and s2, is shown in equation 17 (Mukaka, 2012). It is worth noting that a strong correlation does not imply causality, merely that the two signals change along with, or opposite to, each other.

$$\rho = \frac{\Sigma_{i=1}^{n}((s1_i - \overline{s1})\,(s2_i - \overline{s2}))}{\sqrt{[\Sigma_{i=1}^{n}(s1_i - \overline{s1})^2]\,[\Sigma_{i=1}^{n}(s2_i - \overline{s2})^2]}} \tag{17}$$

4.6. Measuring effects of the strategically weighted vest

The vest, shown in Fig. 2, was weighted in accordance with Motion Therapeutics’ recommended Balance-Based Torso-Weighting (BBTW) assessment approach. The subject was evaluated for response to perturbation at shoulders and pelvis and small weights were chosen, along with the proper location for these weights. Following the assessment, the subject was instructed to wear the vest twice per day for two hours each session, though subjects often wore it for longer or shorter periods of time. With staff assistance, the subject recorded when the vest was put on or taken off. The BBTW assessment was repeated every two weeks and the amount of weight and locations were adjusted as needed. FRAs were also performed at this time.

For a given metric, the time relative to each time the vest is donned (“vest on” event) or doffed (“vest off” event) was computed. These relative times were then binned into 40 bins and the average of each bin was computed. For this study, the width of the analysis window (#bins x bin width) was chosen for each subject to maximize the visibility of the vest's effects. This was done by scanning 50 different bin sizes from 0.375 min up to 18.75 min in 0.375 min steps and selecting the window with the largest number of metrics showing a significant change. If the chosen bin width is too narrow, then the complete effect of the event will not be visualized as the range of the histogram will be smaller than the duration of the event's effects. If the chosen bin width is too wide, there will be some longer term effects that may hide the direct effects of the vest. This could occur if the effects of the event are short lived. The metric could change and return to its pre-event value or to a new value within one or two bin widths. If this were to occur, then it may be difficult to detect the change. An alternative would be to set the window size to a fixed value in order to answer the question “Which metrics show changes within x minutes of the intervention?”.

Fig. 2. An example of strategically weighted vest used in this study – the BalanceWear BW300.

The average values of the metric in each bin were then plotted. A pair of sample plots is shown in Fig. 3. The distributions both before and after the event were tested to determine if they are drawn from a Gaussian distribution using the t-test. The mean histogram value before the event is computed along with the MDC value. The mean value after the event is computed as well and the difference is compared to the MDC value to determine if the changes are significant.

5. Results

5.1. Verifying and validating stride time estimation

5.1.1. Lab based verification

The proposed algorithm was first compared to results obtained from the Vicon® system. The input data consisted of 13 healthy subjects each with 8 walks in our motion capture laboratory. Each walk was captured by 2 different Microsoft Kinect systems and each was filtered with two different algorithms. This resulted in a total of 416 different sets of walk data. As each subject had only 8 walks (each viewed by 2 cameras), walks from all subjects were combined and stride times and step lengths were computed by the Vicon® system and the proposed stride time algorithm for each walk. The difference between the two results was computed and probability density functions were created. The arithmetic mean and the location of the peak in the PDFs were computed and compared. These are shown in Fig. 4.

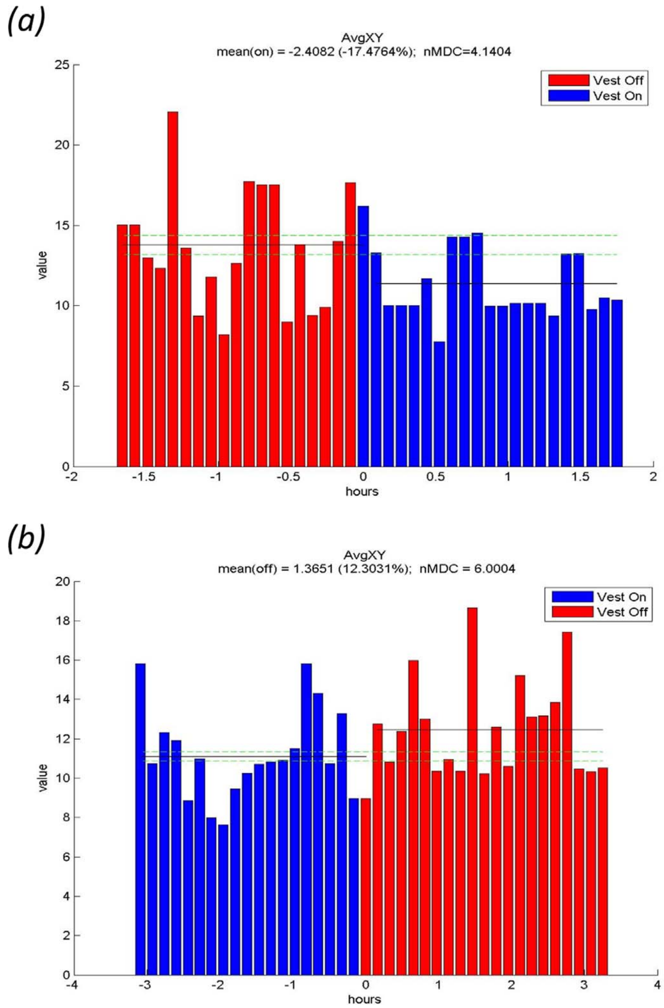

Fig. 3. Plot showing Entropy in the XY direction for subject #1 centered on donning the vest (a) and doffing the vest (b). The plot shows the average step time (in seconds) of all walks that occurred at the time relative to the event shown on the X axis. The solid, horizontal bars represent the mean value of the metric before and after the event. Dashed lines correspond to $+/-$ 1 MDC based upon the pre-event value.

The mean stride time for all walks computed by the Vicon® system was 1.13 s with a standard deviation of 0.101 s. For the proposed algorithm, the mean was 1.11 s with a standard deviation of 0.123 s. The mean error between the two systems was 0.02 s (2.2%) with a standard deviation of 0.160. This shows similar results using both methods on the same data and shows equivalence in the lab. The PDF functions shown in Fig.4 look very similar except for the dual peak around a stride time of 1.15 and a corresponding short and broad peak just to the left of 0.6.

5.1.2. Validation using in home data

A similar approach was applied using data captured from older adult subjects in their homes. The subjects used were all residents of TigerPlace, an independent living community located in Columbia, Missouri. Of the 7 subjects, 3 were male and 4 were female. Ages ranged from a high of 93 years old to a low of 75 years old with an average age of 86. Note that only two of the subjects used for the validation portion of this study were also part of the weighted vest therapy study and are noted by the letter "V" in their designation. As it is not feasible to install a Vicon® system into each apartment, the algorithm developed and validated by E. E, Stone and Skubic (2013) was used as the reference algorithm. The stride time from each suitable walk was computed and compared to the time computed by the reference algorithm for the same walk. This was done for 7 residents individually and the results for each are shown in Table 1. It can be seen that for all seven residents, the mean value of the stride time error for each walk is are less than 0.3%. This demonstrates and validates the proposed algorithm's effectiveness at estimating stride time based upon the movement of the subject's centroid. The mean values for the errors in stride length and average speed for each resident, while not as accurate as stride time, are still within 7.5% and 2.6% of the reference algorithm respectively. These results also show that these algorithms correctly estimate stride length and speed.

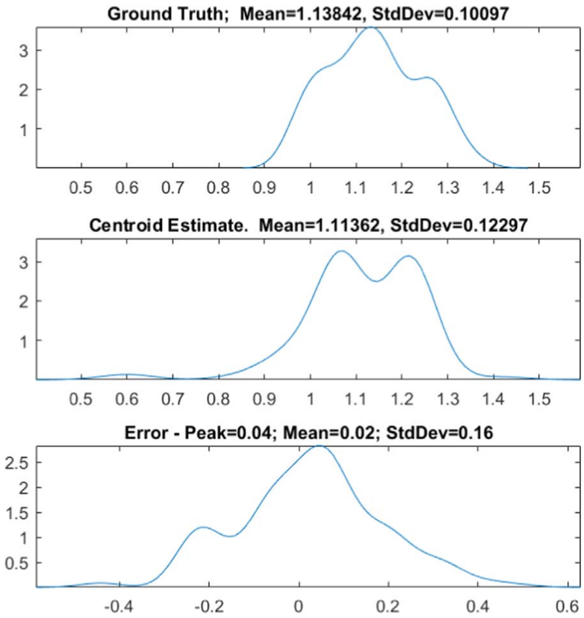

Fig. 4. Laboratory validation of the Stride Time metric. The top graph shows the probability density function PDF for the stride time as detected by the Vicon® system. The middle graph shows the PDF for stride time as computed by the proposed algorithm. The bottom graph shows the PDF of the error values between the two stride time measurements.

5.1.3. Validating to fall risk assessment instruments

Next, we compared each proposed metric to the results of Fall Risk Assessments as well as the individual components of each FRA. The metric values on the three days centered on the day the FRA was conducted are compared against the actual FRA metric. Pearson correlation was performed between the individual metrics and FRA values for each resident individually. In these results, correlations that are not significant ($p > 0.05$) are not included. Table 2 shows those metrics that showed strong correlation ($|\rho| >= 0.40$) for one resident (#1). Metrics related to step time (left, right, and total) have strong correlation with the residents FRA scores for HGS, BBS, TUG, SPPB, and SLS.

Looking at these results across other residents shows a different profile for each resident. This may suggest different disease progressions can amplify different relationships between metrics and their corresponding FRA's. To explore this, the number of strong correlations is tallied across all residents. The results of this analysis are shown in Table 3. While there are many pairs that do not show correlation, all metrics except for trunk sway, show correlation to an established FRA in at least 3 residents. Additionally, all FRA's show correlation to at least 8 metrics. This shows that while the optimal choice of metrics varies from resident to resident, likely based upon their particular medical condition, there are a substantial set of metrics to choose from.

Since the relationship between FRA and the proposed metrics has some dependency on the resident's condition, we aggregated the data for all residents in the hopes of finding some overall correlation between the FRA results and metrics. The results are shown in Table 4. With all patient data aggregated, there is still strong correlation between the Berg Balance Score and the Walk Asymmetry in the Y direction (side-to-side), Habitual Gait Speed and Peak-to-Peak motion in the Y direction and Trunk Sway. Additionally, seven metric-FRA pairs are moderately correlated ($r > 0.3$) with the 26 showing minor or no correlation.

Table 1
In Home Validation Results for the Proposed Metrics.

Subj.	Mean Stride Time Error	Mean Stride Length Error	Mean Speed Error
1	0.101%	−1.93%	−1.85%
2	−0.036%	−7.23%	−1.56%
3	0.001%	−4.67%	−1.98%
4	0.270%	3.13%	−1.38%
5	0.259%	1.24%	−2.18%
V1	0.214%	−1.02%	−2.52%
V2	−0.073%	−6.04%	−2.26%

Results from validation of proposed algorithm using in-home data showing stride time, stride length, and walking speed. Mean Error is the mean of the probability density function of the error between the ground truth and proposed algorithms. Subject numbers starting with a “V” were included in the weighted vest study. Data includes all “purposeful” walks during the study which is variable from subject to subject but ranges from 220 to over 500 days.

Table 2
Correlation Between Proposed Metrics and FRA for Subject #1.

	Side Reach	HGS	BBS	TUG	SPPB	SLS
Speed			0.5163	−0.586		
Ten Foot Walk			−0.5521			
Asymmetry X			0.5582			
Asymmetry Y			−0.6811	0.5872	−0.574	
Stride Length		0.5403				
Stride Time		0.7978		0.7286	−0.7065	−0.6657
Left Step Time		0.7601		0.6612	−0.6463	−0.6638
Right Step Time		0.8109		0.7693	−0.7414	−0.6509
Peak to Peak Z		−0.7494				
Bounce	0.5861	−0.9139				
Entropy Y		0.5304				
Entropy Z	0.6521					

Pearson Correlation "r" values for resident 1 (non-vest). All correlations shown are strong ($|r| > 0.40$) or very strong ($|r| > 0.70$) and all non-zero correlations are significant ($p < 0.05$). Existing Fall Risk Assessments are shown in each column, and metrics developed in this study are shown in rows. Metrics without any correlation are omitted.

5.2. Weighted vest therapy results

With a set of validated metrics that relate to established fall risk assessments, these metrics were studied in the context of the weighted vest therapy on three residents undergoing the therapy. For each resident, histograms similar to Fig. 3 are generated for each metric and the number of "Minimum Detectable Changes (MDC's)" are computed. As can be seen from the Table 5, all of the optimal window sizes for "vest on" events are equal to or shorter than for the corresponding "vest off" events. This suggests that, while variable for each subject, the body's response to putting the vest on is as quick as or quicker than taking the vest off. It also shows that the body's response to the vest is not immediate but requires some time to have an effect.

The results for the subjects participating in the vest study are shown in tabular form in Table 6 and graphically in Fig. 5. Impact is reported in terms of number of MDCs; the value of one MDC is shown in parentheses. These results are referenced throughout the next three sections detailing the results of each subject.

5.2.1. Subject #V1

This subject's gait is described as "stiff and ridged" due to progressive supranuclear palsy. A stiff, rigid gait has characteristically less flexion in the knee joints. This results in a higher than normal amount of centroid movement during ambulation. When this

Table 3
Subjects With Strong Correlation Between Proposed Metrics and FRAs.

	Side Reach	HGS	Funct. Reach	BBS	TUG	SPPB	SLS	MAX	TOT.
Speed	2	1	0	2	3	1	1	3	10
Ten Foot Walk	2	2	0	2	2	1	1	2	10
Walk Efficiency	1	1	1	0	1	0	1	2	5
Asymmetry X	0	1	0	2	1	1	0	2	5
Asymmetry Y	0	0	0	2	2	4	0	4	8
Asymmetry Z	0	1	1	0	0	1	0	1	3
Stride Length	1	2	0	0	0	0	0	2	3
Stride Time	1	3	0	1	2	1	1	3	9
Left Step Time	1	3	0	1	2	1	3	3	11
Right Step Time	1	3	0	1	2	1	1	3	9
P2P X	1	3	2	2	0	1	0	3	10
P2P Y	0	2	1	1	1	2	0	2	7
P2P Z	0	2	1	0	1	0	2	2	6
Step Ratio	0	1	0	0	0	0	2	2	3
Bounce	3	2	2	0	1	0	2	3	10
Sway	1	1	0	0	0	0	0	1	2
Entropy X	0	2	1	1	0	1	0	2	5
Entropy Y	0	2	0	2	0	2	0	2	6
Entropy Z	1	1	1	1	1	0	0	1	5
Entropy XY	1	2	0	1	1	1	0	2	6
Totals	16	35	10	19	20	18	14	45	133

This table shows the number of residents showing strong correlation ($|r| > 0.4$) between the metric (left side) and established Fall Risk Analysis (top row). In this table, the total number of residents was 15. The MAX column shows the maximum number of residents with strong correlation for that metric. The TOTAL column shows the total number of strong correlations for that particular metric. All correlations shown in this table are statistically significant ($p <= 0.05$). All subjects for whom data is shown in this table did not participate in the weighted vest portion of the study.

Table 4
Correlations Between Proposed Metrics and FRAs With Aggregated Data.

	Reach	BBS	TUG	SPPB
Speed		0.206		
Ten Foot Walk		−0.269		−0.246
Walk Efficiency		0.222		0.208
Asymmetry X	0.258	0.258		0.253
Asymmetry Y		0.412	−0.234	0.336
Asymmetry Z			0.206	
Stride Length		0.207		
Stride Time		−0.258		−0.255
Left Step Time		−0.280		−0.274
Right Step Time		−0.235		−0.234
Peak to Peak X		−0.213		−0.261
Peak to Peak Y				−0.213
Entropy XY		0.252		0.201

Pearson correlations between the different FRA instruments and various proposed metrics. Correlations are performed by aggregating metric and FRA pairs for all subjects. Missing cells indicate negligible correlation ($r < 0.20$) or statistically insignificant correlation ($p > 0.05$). Metrics and FRA instruments without any correlations are not shown.

subject donned the weighted vest, the result showed significant decreases in entropy in the Y (−1.78), Z (−1.43), and XY (−2.49) directions. Additionally, the peak-to-peak values also decreased for the Y and Z directions (−1.28 and −1.34 respectively).

When the vest is taken off, entropy in the Y direction returns to close to the original value. In the XY direction, there is a potentially similar increase in entropy though this value is only 0.95 MDC. In the Z direction, entropy further decreased (−1.67) as well as for peak-to-peak in the Z direction (−1.98).

The gait parameters, however, showed a more consistent behavior when used with the vest. When the vest was donned, the subject showed an increase in 10 foot walk time (2.14), a decrease in all both step times (−1.86, and −19.69 for left and right respectively), and −6.25 stride time, stride length (−3.72) and a decrease in walk efficiency (−2.89). Walking speed also decreased by −1.48. All totaled this seems to suggest shorter and more frequent steps. When the vest was removed, all parameters had a significant change in the opposite direction except for both 10 foot walk times.

5.2.2. Subject #V2

Subject number two is characterized by a looser gait. In addition to the clinical assessment, this is confirmed mostly by a decrease in entropy in the X, Z, and combined XY directions (−8.81, −6.21, and −1.17 respectively) when the vest is put on. There is also a reduction in asymmetry in the Y and Z directions (−2.06 and −2.65). Lastly, peak-to-peak motion in the X and Z directions also decreases when the vest is put on (−4.21 and −9.64 respectively). When the vest is removed, the above three entropy values also show significant increase (3.82, 3.86, and 1.77 respectively). Asymmetry in the Y direction does not show any significant change, while Asymmetry in the Z direction does show an increase of 12.62 MDC's. Both peak-to-peak measurements (X and Z directions) show significant increases (1.52 and 1.66) suggesting a partial return towards pre-vest values.

Gait metrics tell a more compelling story. When the vest is put on, significant increases are seen in the 10 foot walk time (1.21), both step times (right (9.14), left (74.92)) and stride time (15.53). When the vest was removed, all of these metrics (except for left step time) showed a significant change back towards the pre-vest value (10 foot Walk: −1.56; step times: $r = -13.71$, $l = -0.37$ (not significant), stride time $= -4.66$). Stride length also showed a significant increase (1.54).

Speed shows a decrease (−1.63 when donned; 2.12 when doffed) which is consistent with an increase and decrease in time needed to walk 10 feet. Walk efficiency increased when the vest was donned (3.81 MDC) and subsequently dropped back beyond initial value when the vest was removed.

5.2.3. Subject #3

Subject #3 also has a looser gait. When the vest was put on, entropy increased in the XY and Z directions (8.55 and 1.80

Table 5
Window Size for Weighted Vest Analysis.

Subject	Vest On Window	Vest Off Window
V1	2 h, 45 min.	4 h
V2	3 h, 30 min.	6 h, 30 min
V3	4 h	4 h

This table shows the optimal analysis window size for each subject and each event. Interestingly, the vest on window is shorter or the same length as the vest off window suggesting a potentially faster response to donning the vest. Also, all of these windows are on the order of a few hours showing, at least for these subjects, that the effects of the vest are not immediate, but take some time to show an effect.

Table 6
Short Term Impact of the Weighted Vest Therapy on the Proposed Metrics.

	V1		V2		V3		V3 (short)	
	Vest On	Vest Off	Vest On	Vest Off	Vest On	Vest Off	Vest On	Vest Off
Speed	−1.48	0.09	−1.63	2.12	2.06	−0.39	−0.51	−2.00
(ft./s)	(0.0231)	(0.0362)	(0.1014)	(0.0815)	(0.0137)	(0.0138)	(0.0335)	(0.0335)
Ten Foot Walk	2.14	−0.81	1.21	−1.56	−1.29	1.05	0.15	1.36
(s)	(0.0541)	(0.0863)	(0.1630)	(0.1404)	(0.0759)	(0.0759)	(0.1731)	(0.1729)
Walk Efficiency	−2.89	3.98	3.81	−6.14	−1.36	−0.05	−0.76	−2.34
	(0.0019)	(0.0016)	(0.0011)	(0.0009)	(0.0021)	(0.0020)	(0.0017)	(0.0017)
asymmetry X	−0.64	5.72	−0.64	−0.87	1.95	2.94	1.10	−1.32
	(0.0009)	(0.0002)	(0.0035)	(0.0036)	(0.0002)	(0.0002)	(0.0006)	(0.0007)
asymmetry Y	−0.83	−1.64	−2.06	−0.78	−1.89	0.14	−16.22	1.12
	(0.0017)	(0.0161)	(0.0089)	(0.0076)	(0.0235)	(0.0235)	(0.0048)	(0.0048)
asymmetry Z	−3.32	−0.12	−2.65	12.62	−1.42	0.02	−5.21	1.16
	(0.0008)	(0.0017)	(0.0054)	(0.0014)	(0.0058)	(0.0050)	(0.0018)	(0.0018)
Stride Length	−3.72	3.40	−0.55	1.54	1.31	−1.33	−0.33	−0.92
(ft)	(0.0224)	(0.0288)	(0.1057)	(0.1039)	(0.0157)	(0.0157)	(0.1068)	(0.1068)
Stride Time	−6.25	3.18	15.53	−4.66	−2.19	0.84	1.18	0.05
(s)	(0.0013)	(0.0073)	(0.0038)	(0.0021)	(0.0067)	(0.0067)	(0.0141)	(0.0145)
Left Step Time	−1.86	2.75	74.92	−0.37	−0.87	0.36	2.55	0.36
(s)	(0.0031)	(0.0085)	(0.0007)	(0.0055)	(0.0123)	(0.0123)	(0.0114)	(0.0112)
Right Step Time	−19.69	3.68	9.14	−13.71	−17.13	6.45	0.26	−0.37
(s)	(0.0006)	(0.0062)	(0.0069)	(0.0013)	(0.0011)	(0.0011)	(0.0170)	(0.0169)
Peak to Peak X	−0.34	−9.42	−4.21	1.52	1.66	−1.04	−0.70	−0.92
(in)	(0.0238)	(0.0268)	(0.0546)	(0.0543)	(0.0605)	(0.0605)	(0.0995)	(0.0995)
Peak to Peak Y	−1.28	0.21	1.14	1.12	−1.39	0.71	−2.39	−2.23
(in)	(0.1755)	(0.2362)	(0.3875)	(0.3537)	(0.2018)	(0.2018)	(0.0624)	(0.0624)
Peak to Peak Z	−1.34	−1.98	−9.64	1.66	2.15	−1.52	−0.90	1.01
(in)	(0.0705)	(0.0720)	(0.0571)	(0.0461)	(0.1150)	(0.1151)	(0.1205)	(0.1206)
Step Ratio	−1.61	−39.97	9.33	−2.69	2.03	2.71	0.75	0.05
	(0.0013)	(0.0000)	(0.0030)	(0.0058)	(0.0012)	(0.0012)	(0.0052)	(0.0052)
Bounce	−7.32	−5.96	−2.66	1.60	4.28	−6.13	−0.10	2.18
(in)	(0.0015)	(0.0051)	(0.0683)	(0.0697)	(0.0105)	(0.0105)	(0.0464)	(0.0467)
Sway	−0.78	0.45	0.25	1.13	−1.98	2.08	−0.74	−0.01
(in)	(0.0561)	(0.0877)	(0.9900)	(0.7589)	(0.1077)	(0.1076)	(0.1045)	(0.1017)
Entropy X	1.73	−9.98	−8.81	3.82	1.65	−1.55	0.01	−0.85
	(0.0250)	(0.0212)	(0.0461)	(0.0393)	(0.0933)	(0.0933)	(0.1200)	(0.1177)
Entropy Y	−1.78	1.46	0.81	1.18	−0.49	0.10	0.63	−1.53
	(0.2316)	(0.2988)	(0.4408)	(0.4392)	(0.4532)	(0.4528)	(0.2658)	(0.2657)
Entropy Z	−1.43	−1.67	−6.21	3.86	1.80	−1.21	2.69	1.22
	(0.1030)	(0.1104)	(0.0743)	(0.0192)	(0.1871)	(0.1871)	(0.1351)	(0.1351)
Entropy XY	−2.49	0.95	−1.17	1.77	8.55	−4.42	0.08	−1.06
	(0.1125)	(0.1963)	(0.3704)	(0.3637)	(0.0239)	(0.0239)	(0.3747)	(0.3741)

Impact on metrics (left column) of the vest therapy for three subjects. Values shown are the number of Minimum Detectable Change intervals represented by the change. The number in parenthesis below each value is the value of one MDC. The units for each metric, applicable to the MDC value, is shown under the name of the proposed metric. "Vest On" refers to the event when the vest is put on, and "Vest Off" refers to the event where the vest is taken off. Therefore, the "Vest On" refers to the change in the proposed metric from when the vest was off to when it was on. * Positive asymmetry values represent a positive change in the absolute value of the metric – towards a more asymmetrical walk. Negative values correspond to a change towards a more symmetrical walk.

respectively). Peak-to-Peak in the Y direction decreased (−1.39) while it increased in the Z direction (2.15). Asymmetry decreased in the Y and Z directions (−1.89 and −1.42 respectively) when the vest was donned. Removing the vest causes a significant change in the opposite direction in entropy XY and Z directions (−4.42 and −1.21) peak-to-peak Z (−1.52) There were no significant changes in Asymmetry Y or Z when the vest was removed.

The temporal parameters showed negative changes in 10 foot walk time, (−1.29), and right step time (−17.13). Positive changes were seen in stride length (1.31). When the vest was taken off, positive changes are seen in both the 10 foot walk (1.05) and right step time (6.45), while a negative change was seen in stride length (−1.33). This subject showed an increase in speed as the vest was put on and a potential, but not significant, drop in speed when it was removed.

For this subject, we also took a brief look at the very short term effect of the vest by looking at only the half hour before and after the vest is donned and doffed. This is shown in table VI and figure 5 as subject "V3 (short)." While most of the metrics did not show any significant change over that short time period, there were significant changes in all three asymmetry metrics. When the vest was put on, asymmetry in the Y and Z directions both decreased (−16.22 and −5.21 respectively) and increased in the X direction (1.10). All three of these metrics changed significantly in the opposite direction (1.12, 1.16, and −1.32 respectively) when the vest was taken off. This result confirms what was seen during development – different metrics change over different periods of time, and that by choosing different time windows, different conditions can be studied.

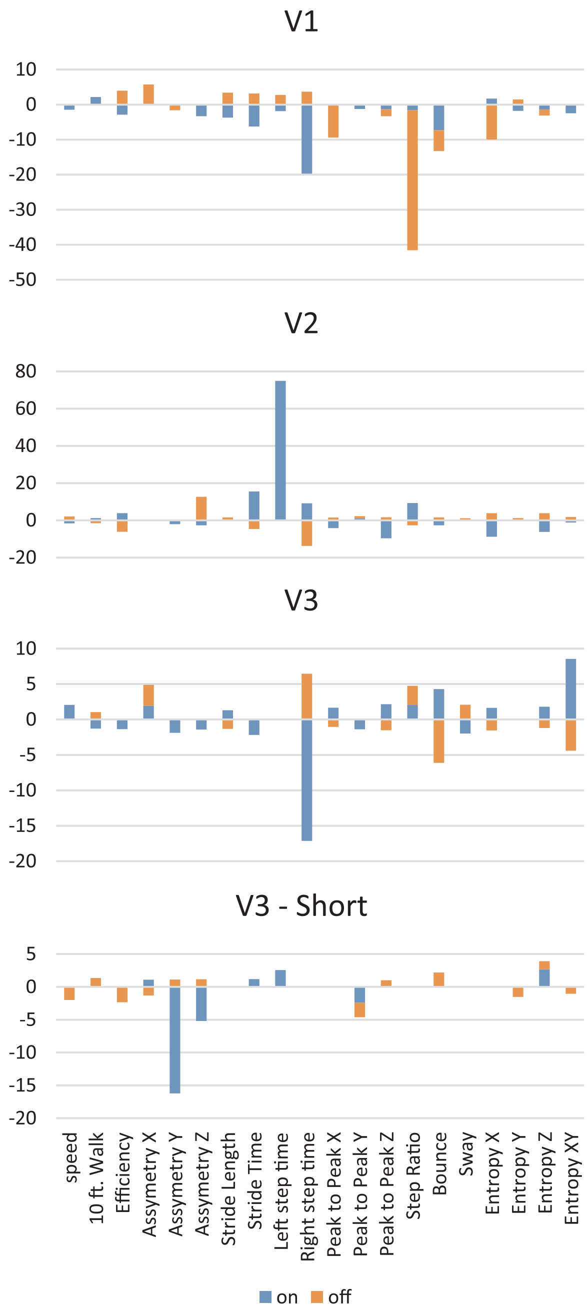

Fig. 5. Graphical representation of the data in Table 6. These figures show the number of MDC's that the metric has changed when the vest is both taken off (red bars) and put on (blue bars). Metrics for which the change is less than one MDC are recorded as zero on these graphs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

5.3. Sensitivity of metrics

Lastly, the sensitivity of each metric was gauged by averaging the absolute value of the MDC changes for all subjects. The results of this analysis are shown in Table 7. From the results shown, for these subjects, the temporal metrics appear to be the most sensitive. Entropy in the X direction and bounce also appear to be more sensitive while peak-to-peak in the Y direction and entropy in the Y direction appear to be the least.

Table 7
Metric Sensitivity.

	Sensitivity On	Sensitivity Off
Speed	1.72	0.87
Ten Foot Walk	1.55	1.14
Walk Efficiency	2.69	3.39
Asymmetry X	1.08	3.18
Asymmetry Y	1.59	0.85
Asymmetry Z	2.46	4.25
Stride Length	1.86	2.09
Stride Time	7.99	2.89
Peak to Peak X	2.07	3.99
Peak to Peak Y	1.27	0.68
Peak to Peak Z	4.38	1.72
Left Step Time	25.88	1.16
Right Step Time	15.32	7.95
Step Ratio	4.32	15.12
Bounce	4.75	4.56
Sway	1.00	1.22
Entropy X	4.06	5.12
Entropy Y	1.03	0.91
Entropy Z	3.15	2.25
Entropy XY	4.07	2.38

Sensitivity of each Metric for all three subjects. This table shows the average number of MDC's registered by each metric for all residents. From the results obtained, the most sensitive metrics are the temporal metrics, particularly left and right step time, step ratio, average step time. Of the more sensitive metrics, most are more sensitive to the vest on event than the vest off event.

6. Discussion

6.1. Validation

The proposed stride time algorithm scored within 2% of the Vicon® generated results with 13 different subjects with multiple walks. Next, the stride time algorithm was tested against a validated reference algorithm using data obtained from in home subjects captured in the subject's home. Data from seven subjects were selected and all had less than 0.26% error in the mean value of stride time. Stride length and average speed, while slightly less accurate, were still accurate within 7% and 3% respectively.

6.2. Relationship to FRA

Comparisons to existing FRA's were done to assess the potential of comparing these metrics to clinical fall risk assessments. Each individual subject had a different set of correlation values between the set of metrics and FRA results. While you would expect, and we have seen in Tables 2 and 3, some relationship between step time and the TUG test, the TUG test includes a requirement for the subject to execute a 180 degree turn. The ability to execute a proper 180 degree turn depends on the subject's ability to balance. This would suggest some relationship between the TUG and balance measurements. As also seen in Table 2, there is a strong negative correlation between the BBS score and asymmetry as well as a positive correlation between TUG and asymmetry. This confirms, at least in this subject, that the BBS and TUG measure common components of gait.

The relationship between FRA's and metrics are, however, different between different subjects. The results in Table 3 show that, while not every metric relates to each FRA in the patient population, there is enough overlap between these to show several FRA's correlating to several proposed metrics. As each subject has a different set of symptoms that will impact balance and/or gait, you would expect each subject to have a different set of correlations. Table 3 shows the smallest set of correlations between the metrics and the functional reach FRA. The largest set of correlations is shown for Habitual Gait Speed. Similarly, the metrics with the most overlap with FRA's are Step times, 10 foot walk, speed and peak-to-peak in the Y direction.

6.3. Use with the weighted vest

Lastly, this full set of metrics was used to study the weighted vest therapy on 3 different subjects. Overall, the changes in these metrics are consistent with expected changes based upon the subject's physical condition.

6.3.1. Subject V1

For the rigid gait of subject #V1, the weighted vest caused a decrease in lateral entropy followed by an increase when the vest was removed. This is backed up by a decrease in peak-to-peak movement in the Y direction. Looking at all of the changed temporal metrics together, a picture of the effect on the subject starts to appear. The 10 foot walk time metric increased and overall speed decreased. This is, at first glance, counter-intuitive as you may expect an increase in walk speed as the subject's ability to ambulate "improves". Factoring in stride length, stride time, right step time, and left step time, paints a picture of a subject taking shorter, quicker steps. Lastly, the subject's walk efficiency is shown to drop when the vest is donned and increase when the vest is removed.

With the vest removed, entropy in the Y direction, stride length, all both step times (left, right), and stride time changed back towards their values before the vest was put on. Speed, 10 foot walk, and peak-to-peak in the Y direction had very little change when the vest was removed suggesting a possible residual effect of the vest therapy after the vest is removed.

6.3.2. Subject V2

Subject V2 also shows an increase in the 10 foot walk times and a reduction in speed when the vest is donned. Additionally, right and left step times and stride time increase with a slight, but not statistically significant, decrease in stride length. Looked at together, this indicates slower, more deliberate steps of the similar length. The subject's walk becomes more efficient, even with a small but significant increase in peak-to-peak motion in the Y direction suggesting that additional "rocking" or swaying during the walk might improve the overall directness of the walking path. A drop in entropy in the X and XY directions suggest a smoother walk as a result of the therapy as does the decrease in peak-to-peak motion in the X direction.

For virtually all of the metrics discussed, removing the vest causes a change in the opposite direction except for left step time which, while showing a decrease, was not a significant change. Removing the vest also caused a significant increase in stride length. This suggests a smaller residual effect of the vest on this particular subject.

6.3.3. Subject V3

The addition of the 30 min. window analysis showed a difference in the progression of the vest therapy on different parameters. This run suggests that, for this subject, all three asymmetry metrics change quickly when the vest is donned and doffed. Few of the remaining metrics had any significant change when the vest was donned while more had changed significantly when the vest was removed. Using a window size of 3 h (more in line with the other two subjects), a much larger group of metrics show significant changes. The three asymmetry metrics still show changes when the vest is donned, but no longer show a significant change when the vest is doffed.

The longer term window showed a decrease in the 10 foot walk time, and an increase in speed. It also showed an increase in stride length and a decrease in stride time, although the decrease in left step time was not significant. Taken together, this shows the subject is simply walking faster with longer and quicker steps. Asymmetry in the Y and Z directions decrease (though there is no significant return to previous values with the longer window).

6.4. Limitations

Two limitations with using centroid based metrics involve multiple subjects and large obstructions. If two or more people are routinely present in the monitored area, it is necessary to separate them before analysis can be done. In this study, the Gaussian Mixture Model clustering algorithm was able to adequately separate people with significantly different height and/or walking speeds. Of the four total subjects who participated in the strategically weighted vest study, the data from one was omitted from this study. The subject had a similar height and walking speed as another person who was frequently in the apartment. The clustering algorithm was unable to separate these two people's walks adequately. An improved clustering algorithm combined with a different feature set will be tried in the hopes of better separating the walks by each person.

A second limitation is large obstructions. One of the benefits of using the centroid to compute gait parameters is the ability to monitor even if the subject's feet are obstructed. A typically cluttered living area may have foot stools, ottomans, or coffee tables which may, from time to time, obstruct the subject's feet. Using centroids to compute gait parameters reduces the impact of these obstructions on generating reliable metrics. Larger obstructions, however, may negatively impact the computation of these metrics. If enough of the subject is obstructed, the size of the point cloud used to compute the centroids may be small enough to cause distortions to the calculated metrics. This can be addressed by applying a minimum size threshold to the point cloud and rejecting all walks for which the point cloud is too small.

7. Conclusions

A toolbox of metrics and analysis approaches are presented that can be used to study intervention effects on gait. The large assortment of metrics allows a clinician to choose which metric(s) to use based upon what is being studied. For example, if a TUG test shows a change, these metrics can be used to determine if it was due to a change in stride time, stride length, or entropy (suggesting balance). Comparing these metrics against established FRAs shows strong to very strong correlation. These correlations, however, appear to be dependent upon the subject's individual physical condition and, potentially, disease state. The relationships are consistent with the components of both the FRA instruments and the physical and physiological components of the metrics. When aggregated across all subjects, three metric/FRA pairs showed strong correlation, 4 show moderate correlation, and 25 show weak correlation.

Results also show that response to the strategically weighted vest therapy is not immediate but, at least for these subjects, requires time on the order of a few hours to reach full effect. These results also show that the body responds as quickly or more quickly to the vest being donned than when the vest is removed. These results also show that the algorithm can be used to determine the effects on each metric over specific periods following the events. In other words, it can be used to answer the question "Which metrics show the most change within 1 h of the vest being taken off".

Finally, the metrics previously presented in Wallace et al. (2013) are now presented in the larger context of temporal metrics and overall subject gait. The results of three participants in the weighted vest study, each with unique physical conditions, demonstrate the ability of these metrics to identify changes in the subject's ambulation as a result of the vest therapy. The results also show that the subject shows significant changes in some metrics soon after donning the vest, while other metrics are slower to respond. Future work will include study into the long term effects, measured over days and weeks, of the vest therapy as well as shorter term effects of the vest on these aspects of the subject's gait. It will also study, more in depth, the relationship between FRA's and these metrics. Results also suggest that the temporal metrics are the most sensitive to changes following wearing or removal of the vest.

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Appendix A

Variable Names

What follows is a list of all of the variables used throughout this paper and their meanings. Unless qualified as pertaining to a particular computation in the table, variables names and their usage are consistent throughout all formulae.

x, y, z	Actual centroid location in the X (along the direction of travel), Y (perpendicular to X in the horizontal plane), and Z (up / down) directions.
x', y', z'	Expected location of the centroid in the walking path. To compute this, a best fit line is determined over +/- 0.5 seconds centered on the current point. Using the line, the centroid location at time = t + 1 is determined.
δ_i	Error between the expected location and actual location of the centroid in the *i* direction.
A_i	Asymmetry in the *i* direction.
$p2p_i$	Peak to Peak travel in the *i* directions.
s	Walking speed.
W	Ten Foot Walk Time
T	Duration of the walk
D	Distance of the walk.
E	Walk Efficiency
$H_{DTE}^{\delta_i}$	Deluca & Termini computed entropy in the *i* direction.
$H_{PPE}^{\delta_i}$	Pal computed entropy in the *i* direction.
$H_{\alpha QE}^{\delta_i}$	Pal and Bezdek computed entropy in the *i* direction
δ_{kj}	For entropy calculations, centroid position *j* in the *k* direction.
K	For entropy calculations, a normalization constant chosen to be 1 in this paper.
α	For Pal-Bezdek entropy calculations, this controls the sensitivity of the entropy value to changes in the input data. Set to 0.75 for this paper.
$\boldsymbol{M}$	Vector containing the time indices of all the local minima in the δ_z signal.
ST1, ST2	Temporary values of step time during the calculation of left and right step time. Based upon the direction of the first peak (either left or right) these are assigned to be left and right step time.
B	Bounce measurement in gait.
S	Trunk sway measurement in gait.
MDC	Minimum Detectable Change. MDC corresponds to the smallest change that can be detected which cannot be attributed to random error.
MSE	Mean Squared Error estimated by the variance for the pre-event distribution.

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