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## Local Dynamic Stability Assessment of Motion Impaired Elderly Using Electronic Textile Pants

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### Abstract

A clear association has been demonstrated between gait stability and falls in the elderly. Integration of wearable computing and human dynamic stability measures into home automation systems may help differentiate fall-prone individuals in a residential environment. The objective of the current study was to evaluate the capability of a pair of electronic textile (e-textile) pants system to assess local dynamic stability and to differentiate motion-impaired elderly from their healthy counterparts. A pair of e-textile pants comprised of numerous e-TAGs at locations corresponding to lower extremity joints was developed to collect acceleration, angular velocity and piezoelectric data. Four motion-impaired elderly together with nine healthy individuals (both young and old) participated in treadmill walking with a motion capture system simultaneously collecting kinematic data. Local dynamic stability, characterized by maximum Lyapunov exponent, was computed based on vertical acceleration and angular velocity at lower extremity joints for the measurements from both e-textile and motion capture systems. Results indicated that the motion-impaired elderly had significantly higher maximum Lyapunov exponents (computed from vertical acceleration data) than healthy individuals at the right ankle and hip joints. In addition, maximum Lyapunov exponents assessed by the motion capture system were found to be significantly higher than those assessed by the e-textile system. Despite the difference between these measurement techniques, attaching accelerometers at the ankle and hip joints was shown to be an effective sensor configuration. It was concluded that the e-textile pants system, via dynamic stability assessment, has the potential to identify motion-impaired elderly.

### Index Terms

E-textile; local dynamic stability; slips and falls; wearable computing

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*Note to Practitioners*—This paper presents an e-textile system with embedded e-TAGs and a fall risk assessment algorithm using local dynamic stability. By identifying the individuals with higher risk of falling, it is possible to prevent and/or reduce the injuries associated with fall accidents.

## I. Introduction

Injuries from slip-and-fall accidents have been recognized as a prevalent problem, especially for the elderly. Approximately one-third of adults over 70 years of age fall in a given year, with one-fourth of those falls resulting in fall-related injuries [1]. Thus, the elderly, especially those living independently in a home environment, are in a great need of effective fall prevention, detection, and intervention solutions.

Age- and disease-associated degradation of an individual's ability to ambulate in a repetitive and stable manner is regarded as an apparent sign of many gait pathologies leading to falls. It was suggested that individuals with step variability fell more often than nonfallers in a study of older adults who were hospitalized after falls [2]. Furthermore, researchers also demonstrated that gait variability was linked to falls in the elderly [3]. Therefore, effective and timely assessment of gait stability of the elderly could help detect individual changes in stability and differentiate fall-prone individuals with higher instability.

Local dynamic stability measure, which is based on the nonlinear dynamic theory, has been proposed as a more precise measurement of individuals' resistance to perturbations. Using the dynamic stability concept, Dingwell and Cusumano [4] successfully explained that individuals with pathological gait exhibited a slowdown adaptation to increase their stability, and clearly demonstrated the differences between dynamic stability and conventional gait variability measurements. This dynamic stability measure was also shown to be able to detect the influences of external conditions, like treadmill walking and over ground walking [5]. Presently, however, the application of local dynamic stability is still constrained in the laboratory with no attempt for everyday field assessment, which is greatly needed for fall prevention solutions.

Wearable computing via ambulatory sensors started to receive attention in the area of home automation. Wearable systems have the advantages that they can be worn during activities of daily living without being tethered, and can be used for continuous health status monitoring, disease prevention, early diagnosis, etc. [6]. From the perspective of maximizing the user compliance, wearable systems can be embedded into various forms including clothing [7], [8] and jewelry [9]. From the application perspective, specific to fall accidents prevention, various designs utilizing ambulatory sensors have been proposed to demonstrate the feasibility to detect fall events from daily activities [8], [10], [11]. Developments of fall event detection system show promising potential in terms of reducing injuries resulting from fall accidents in a home living environment.

Ambulatory fall risk assessment is an important research direction, as part of the early diagnosis application of the telemonitoring system. Compared to the fall detection literature, studies relevant to the ambulatory fall risk assessment are scattered [12], [13]. Their performances in fall risk prediction are also limited, possibly due to the linear approach to assess postural stability [4]. Because it is possible to uncover the underlying motor control dynamics using nonlinear dynamics approach, it is important to investigate whether the combination of local dynamic stability and the wearable computing technology could be a viable solution in terms of identifying or differentiating individuals with higher risk of falling. Such solution can be easily integrated into a wireless home surveillance network to offer medical assistance to individuals deemed with risk of falling.

Therefore, the purpose of the current study was to demonstrate the feasibility of an e-textile pants system in differentiating motion-impaired individuals, via a local dynamic stability algorithm. Specifically, we were trying to assess the effectiveness of local dynamic stability, indicated by maximum Lyapunov exponent (refers to the finite-time local dynamic stability in this document unless specified otherwise), computed from both the motion capture (as a

baseline measurement) and e-textile systems in differentiating three diverse groups with different physical characteristics. This study was intended to provide the proof of concept for assessing fall risks utilizing our e-textile system and local dynamic stability algorithm.

## II. Methods

### A. Instrument and Procedure

A pair of e-textile pants (one size) was developed to collect acceleration, angular velocity, and piezoelectric data. These e-textile pants (Fig. 1) were in the form of special textile, embedded with numerous e-TAGs which are small printed circuit boards with some combination of microcontrollers, sensors, and communication devices [14]. Each e-TAG has an Atmel AVR Atmega8 microcontroller with a built-in I<sup>2</sup>C interface and 10-bit analog-to-digital converter [15]. These e-textile pants have four main types of e-TAGs. Four gyroscope/accelerometer e-TAGs consisting of an ADXL203 accelerometer (range =  $\pm 1.7$  g, sensitivity = 1 mV/mg, noise level = 1 mVrms) and ADXRS300 gyroscope (range =  $\pm 300^\circ$ /s, sensitivity = 5 mV/ $^\circ$ /s, noise density = 0.1 $^\circ$ /s/rtHz) [16], [17] were attached near the ankles and the knees of the participant wearing the e-textile. There were also two e-TAGs attached to the participant's hips with the same accelerometers but without the gyroscope. To aid in heel contact detection, each foot had a piezoelectric sensor attached to the heel that was connected to an e-TAG close to the ankle on the pants [18]. Each gyroscope/accelerometer was sampled by its microcontroller at 125 Hz. The piezoelectric sensors were sampled at 750 Hz. Choice of these specific sampling rates was made both to accommodate the initial hardware development and to sufficiently measure the characteristics of daily activities, which is generally below 15 Hz [19]. All data was then transmitted over the I<sup>2</sup>C network to a final Bluetooth e-TAG, which then wirelessly transmitted the data to a host computer for further processing.

Ten infrared-reflective markers were placed bilaterally over bony landmarks of the participant's lower extremities (distal head of the second metatarsal/heel/lateral malleolus/lateral epicondyle/ASIS) for kinematic motion capture with a six-camera ProReflex system (Qualysis Medical AB, Gothenburg, Sweden). The sampling rate for the motion capture system was 120 Hz. An overhead safety harness system was used to protect participants from accidentally losing balance while walking on the treadmill.

Before the data collection, each participant was allowed up to 5 min to familiarize themselves on the Parker PM treadmill (Parker Treadmill Company, Auburn, AL). Participants selected their own preferred speed at which they felt comfortable to swing their arms naturally without requiring the use of the handrails on the treadmill. This speed was then used as the 100% normal walking speed for that participant. During the data collection, participants were instructed to walk on the treadmill at the speed remotely controlled by the experimenter. Three speed levels (100%, 110%, and 120% of the individual's normal speed) were tested for each participant sequentially. At each speed level, a 50-s dataset was taken by both motion capture system (MT) and e-textile system (ET) simultaneously. Synchronization between motion capture system and e-textile system was achieved by a significant right heel contact made intentionally by each participant before each walking trial.

### B. Local Dynamics Stability Computation

Local dynamic stability was quantified by the maximum Lyapunov Exponent (maxLE) from a nonlinear dynamics approach. Briefly, each experimental time series measurement (e.g., acceleration measures at right hip joint) can be reconstructed into a state space with sufficient dimensions to describe the target dynamic system unambiguously [4]. A state space is a space defined by the independent coordinates (dimensions) required to describe the target dynamic motion. Though different assessment methods can be used to construct such a state space, the

most commonly used one is the so-called time-delayed coordinate method [20]. The time-delayed coordinate vector can be defined as

$$y_n(d) = \{s(t_0 + n\tau_s), s(t_0 + n\tau_s + k\tau_s), \dots, s(t_0 + n\tau_s + k(d-1)\tau_s)\} \quad n=1, 2, \dots, d \quad (1)$$

where  $s$  is the original time series data,  $t_0$  is the initial time of the time series data,  $\tau = k\tau_s$  is an appropriately chosen time delay,  $\tau_s$  is the minimum sampling interval (1/120 s in our case),  $n$  indicates each dimension of  $y$ , and the integer  $d$  is the embedding dimension. The two unknown parameters, time delay  $\tau$  and the embedding dimension  $d$ , can be estimated by using the auto mutual information approach [21] and nearest false neighbors approach [22], respectively.

Small perturbations to the dynamic system can be represented as neighboring trajectories deviating from the original trajectory in a state space. In the context of gait studies, such perturbations appeared as step-to-step variability and thus are referred to as local perturbations [4]. The Lyapunov exponents (also known as characteristic exponents) of a trajectory are the measure of the average rate of expansion or contraction of nearby trajectories. The maxLE, denoted as  $\lambda_{max}$ , can be defined as

$$d(t) = D e^{\lambda_{max} t} \quad (2)$$

where  $d(t)$  is the average Euclidean distance between neighboring trajectories in a state space of a given dynamic system at time  $t$ , and  $D$  is the initial separation between these trajectories [4]. Regarding finite experimental time series data with noise embedded, Rosenstein's algorithm [23] can be employed to estimate  $\lambda_{max}$  considering its demonstrated appropriateness for finite-size experimental datasets. Taking the log of both sides, the above equation can be approximated as

$$\ln[d_j(i)] \approx \lambda_{max}(i\Delta t) + \ln[D_j] \quad (3)$$

where  $d_j(i)$  is the Euclidean distance between the  $j$ th pair of neighboring points at  $i$ th steps. The variable  $\lambda_{max}$  is then approximated.

### C Participants

Five healthy young, four healthy elderly, and four motion-impaired elderly individuals participated in the current study. Their anthropometric information is summarized in Table I. Informed consent was reviewed by the IRB at Virginia Tech and obtained from each participant prior to data collection. Motion-impaired elderly were selected based on previous gait perturbation analysis [24], [25] (i.e., these individuals fell when their gait was purposefully perturbed) and self-reported medical history, and identified as frequent fallers. Self-report medical questionnaires also indicated they had recent histories of falling.

### D. Data Analysis

From the e-textile system, sagittal angular velocity (AV) was measured at ankle and knee joints on both sides, while vertical acceleration (VA) was measured at ankle, knee, and hip joints on both sides. From the motion capture system, corresponding to the e-textile system, sagittal angular velocity was derived at ankle and knee joints on both sides, and vertical acceleration was derived at ankle, knee, and hip joints on both sides. Kinematic measurements from the

motion capture system and accelerometer and gyroscope measurements from the e-textile system were filtered using a fourth-order Butterworth low-pass filter with a cutoff frequency of 6 Hz. The state space for each data trajectory was constructed using five embedding dimensions and a 6-frame (i.e., 0.05 s) time delay. MaxLE was computed during the first 200 frames (about 0~ 1 stride) for each data trajectory [4]. Altogether, 20 maxLE were obtained per each trial/participant. All of the computations were performed in MATLAB 7.0 (The MathWorks Inc., Natick, MA) and TSTool [26].

Two-way analysis of variance (ANOVA) on maxLE was performed with group as the between-subject variable and system as the within-subject variable. The group variable had three levels: healthy young (HY), healthy elderly (HO), and motion-impaired elderly (UO). The system variable had two levels: motion capture system (MT) and e-textile system (ET). The above ANOVA tests were performed by different conditions (joint, parameter, and speed). Conditions included six joints (ankle, knee, and hip for each leg), two parameters (angular velocity and vertical acceleration), and three speeds (100%, 110%, and 120% of normal speed). Post-hoc tests of group effect were then performed using a Tukey-Kramer HSD test. All statistical analyses were performed in JMP 6.0 (SAS Institute, Inc.). To reduce the possible inflated Type I error due to multiple tests, a conservative significance level of  $p < 0.01$  was used across all the tests.

### III. Results

#### A. Speed Condition #1 (100% of Normal Speed)

**MaxLE Computed From Vertical Acceleration (VA)**—Significant system effects (i.e., e-textile versus motion analysis) on maxLE were found at the left ankle ( $p = 0.0048$ ), right ankle ( $p = 0.0134$ ), and left knee ( $p = 0.0040$ ) joints. At all three locations, maxLE assessed by the MT system was significantly higher than that assessed by the ET system (Fig. 2).

Significant group effects (i.e., HY versus HO versus UO) on maxLE were found at three locations: right ankle ( $p = 0.0008$ ), left hip ( $p = 0.0027$ ), and right hip ( $p = 0.0014$ ) joints. Follow-up Tukey-Kramer HSD tests indicated that the maxLE measurements for the motion-impaired elderly were significantly higher than either of the other two groups when using the MT system only (Fig. 2). This result confirmed that motion-impaired elderly had degraded local dynamic stability compared to the healthy individuals.

**MaxLE Computed From Angular Velocity (AV)**—Significant system effects on maxLE were found at both left ( $p = 0.0016$ ) and right ( $p = 0.0091$ ) knee joints. At both locations, maxLE assessed by the MT system was significantly higher than the ET system (Fig. 3).

Contrary to VA-based maxLE, no significant group effect on AV-based maxLE was found in any of the four locations (left and right ankle, left and right knee).

#### B. Speed Condition #2 (110% of Normal Speed)

**MaxLE Computed From Vertical Acceleration**—Similar to speed condition #1, significant system effects on maxLE were found at the left ankle ( $p = 0.0002$ ), right ankle ( $p = 0.0061$ ), and left knee ( $p < 0.0001$ ) joints. At all three locations, maxLE assessed by the MT system was always significantly higher than the ET system (Fig. 4).

Unlike speed condition #1, a significant group effect on maxLE was only found at the right ankle joint. Follow-up Tukey-Kramer HSD tests indicated that in both ET and MT systems, maxLE produced by the motion-impaired elderly group was significantly higher than that produced by the other two groups (Fig. 4). This result suggested that motion-impaired elderly had considerable instability compared to the healthy individuals.

**MaxLE Computed From Angular Velocity (AV)**—Unlike speed condition #1, a significant system effect on maxLE was only found at the right knee joint ( $p = 0.0054$ ). MaxLE assessed by the MT system was significantly higher than the ET system (Fig. 5).

No significant group effect was found in any of the four locations (left and right ankle, left and right knee).

### C. Speed Condition #3 (120% of Normal Speed)

**MaxLE Computed From Vertical Acceleration (VA)**—Similar to speed conditions #1 and #2, significant system effects on maxLE were found at the left ankle ( $p = 0.0064$ ), right ankle ( $p = 0.0002$ ), and left knee ( $p = 0.0048$ ) joints. At all three locations, maxLE assessed by the MT system was always significantly higher than the ET system (Fig. 6).

Just as with speed condition #2, the right ankle joint was the only location where a significant group effect on maxLE was evident. Follow-up Tukey-Kramer HSD tests indicated that in the ET system, maxLE produced by the motion-impaired elderly group was significantly higher than that produced by the other two groups (Fig. 6). With the MT system, the motion-impaired elderly group was found to have significantly higher maxLE than the healthy elderly group. This result indicated a reduced local dynamic stability for the motion-impaired elderly.

**MaxLE Computed From Angular Velocity (AV)**—Similar to speed condition #1, significant system effects on maxLE were found at both left ( $p = 0.0025$ ) and right ( $p < 0.0001$ ) knee joints. MaxLE assessed by the MT system was significantly higher than that assessed by the ET system (Fig. 7). Still, no significant group effect was found in any of the four locations (left and right ankle, left and right knee).

### D. Interaction Effect

No significant interaction effect was found between the measurement system and the participant groups.

## IV. Discussions and Conclusion

The objective of current study was to evaluate the performance of local dynamic stability (indicated by maximum Lyapunov exponent) in differentiating motion-impaired elderly, and the integration of local dynamic stability assessment with the e-textile pants system. The main contributions of the current study were 1) to demonstrate the feasibility to assess risk of falling via an e-textile pants system and 2) to investigate the effect of the sensor configuration on the assessment performance. Compared to our previous publication [27], which was a simulation study of estimating gait parameters using e-textile system, the current study empirically investigated the capability of e-textile to assess the risk of falling. The knowledge obtained in the current study can be used to facilitate the further refinement of a specific wearable fall risk assessment system, which can be easily integrated into a home automation system via wireless networking.

In the current study, local dynamic stability was shown to successfully differentiate the motion-impaired elderly from the healthy individuals. Vertical acceleration-based maxLEs were found to be significantly affected by different groups at several joint locations. These locations included the right ankle and left and right hip joints. The motion-impaired elderly was always found to have higher maxLE (which means lower local dynamic stability) than both the healthy young and healthy elderly subjects. By definition, local dynamic stability quantifies the sensitivity of the system to infinitesimal perturbations [5]. In terms of human walking, local dynamic stability may indicate how well the human motor control system dynamically resists

and compensates for the small perturbations within and between gait cycles. Such perturbations may come from intrinsic motor control error and extrinsic factors like uneven surfaces [4]. Contrary to Floquet multiplier measures, which quantify the stability at certain critical events like heel contact and toe off [28], maxLE measures dynamic stability in general taking into account both the spatial variability and the associated temporal variability, as opposed to linear averaging approach. Considering the results from the current study, it can be confirmed that the ability of the frail elderly to handle small stride-to-stride perturbations has been degraded. These results also supported the effectiveness of utilizing acceleration-based local dynamic stability to differentiate the motion-impaired elderly despite the fact that angular velocity-based dynamic stability could not distinguish between groups. Local dynamic stability measures assessed from accelerometer data have been quite successful in terms of characterizing and differentiating disease and control groups [4], over-ground walking and treadmill walking [5], etc. Overall, the accelerometer could be regarded as an effective measurement tool to differentiate diverse groups when paired with dynamic stability assessment.

Walking at one's normal speed represents an ideal condition to implement the assessment of risk of falling via local dynamic stability. England and Granata [29] indicated that the local dynamic stability will decrease with reducing walking speed for the younger individuals. The results from the current study suggested that the local dynamic stability measures can differentiate the fall-prone elderly at more locations (i.e., right ankle, left and right hips) under 100% speed condition than under 110% and 120% speed conditions (i.e. right ankle). This finding is useful to the actual design of a fall risk assessment system as it is possible to design a system with redundancy or various designs with different choices of sensor locations.

The obtained dynamic stability was found to be influenced by the measurement system. At left and right ankle and hip joints, maxLE assessed by the e-textile system tended to be lower than that assessed by the motion capture system. However, within each system, a similar trend was observed in that maxLE for the motion-impaired elderly was higher than for the other two groups. This finding demonstrated the potential utility of the current e-textile system in assessing dynamic stability. The apparent discrepancy between the assessed local dynamic stability from these two systems might be mainly due to different levels of data manipulation adopted in different systems [30]. The angular velocity and vertical acceleration from the e-textile system came from the direct measurement of the gyroscope and accelerometer with necessary coordinate transformation. The angular velocity and vertical acceleration from the motion capture system, however, was derived from marker position data via numerical differentiation and other data analysis processes. As such, the maxLE assessed from different systems were not expected to be identical. Despite the maxLE discrepancies, however, the current e-textile system was still shown to be as effective as the motion capture system in differentiating motion-impaired elderly.

In terms of differentiating motion-impaired elderly via dynamic stability, the most effective sensor locations were found to be the right ankle and left and right hips. The left ankle also showed the potential to be an effective sensor placement site, considering its very low  $p$ -value. Previous studies [5] usually attached sensors at the lower back or waist region, based on the rationale that those places were the closest representatives of the whole body center-of-mass (COM) and also had lower user compliance. Such rationale could also be used to explain the effectiveness of sensor placement at hip joints in the current study. Besides hip joints, ankle joints were also found to have similar differentiating capabilities in the current study. The fact that both ankle and hip joints were effective sensor placement sites had two implications. First, in certain scenarios where the lower back or waist regions are not approachable, it is still possible to identify motion-impaired elderly from sensors attached at ankle joints. Second, in scenarios where multiple sensor configurations could be readily achieved (like using an e-

textile pants system), sensors placed at both ankle and hip joints could provide measurement redundancy for improved accuracy and reliability.

Several limitations and assumptions existed in the current study. First, sample size in the current study was limited, though some promising results were still obtained. A future large scale study involving more participants is desired to substantiate current findings. Second, there were underlying issues associated with dynamic stability computation such as the optimal choice of embedding dimension, time delay, prediction window, length of data set, etc. [4]. From the computation perspective, both the embedding dimension and the time delay have to be chosen carefully in order to faithfully reconstruct the underlying dynamics of interest. It has been numerically demonstrated, however, that the maxLE error associated with varying embedding dimensions and time delays was less than  $\pm 10\%$ , and most errors were less than  $\pm 5\%$  [23]. Thus it was concluded that the computation of maxLE would not be extremely sensitive to the selection of embedding dimension and time delay [23]. The length of the data set may be another confounding variable for the reliability of maxLE computation. It has been found that the value of maxLE stabilizes after 35 gait cycles [31]. Each dataset in the current study corresponded to approximately 45 gait cycles, which should be sufficient for reliable maxLE computation. Third, participant anthropometric differences (e.g. the motion-impaired group weighed on average 17.4 kg more than the other groups) were not strictly controlled in the current study. Though we have no reason to believe such anthropometric differences may confound the obtained results considerably, a future study with a more homogenous participant group is desired to increase the external validity. In addition, walking speed standardization was based on individual's comfortable normal speed, rather than the absolute uniform speed.

To our knowledge, the current study is the first attempt to integrate the dynamic stability assessment into an e-textile system. Automatic spatio-temporal gait parameter detection via portable sensors is not a brand new concept. For example, Williamson and Andrews [32] have successfully utilized shank-mounted accelerometers to perform real-time gait event detection together with various algorithms including rough sets and adaptive logic networks. More recently, Pappas *et al.* [33] developed a portable gait phase detection system composed of gyroscopes and force-resistive sensors. By incorporating the force-resistive sensors, their system was insensitive to deviations from normal walking and nonwalking activities. Compared to previous portable systems, the obvious benefit of the e-textile pants is in enhancing the user compliance due to its clothing-like form factor, and the possibility of incorporating multiple sensors without comprising the user compliance. Promoting the current e-textile system from the hardware development stage to lab testing with target population is also an improvement compared to previous studies. In the future, the proposed system can be implemented in daily living according to the existing two telemonitoring application models [34]. First is to utilize the wellness and disease management model, in which the users will actively initiate a consistent walking trial for computing the maxLE. Second is to apply the independent living and remote monitoring model, in which the medical personnel instead of the user will remotely instruct and initiate a walking trial to monitor the falling risk of the user.

The e-textile pants together with dynamic stability assessment capabilities are relevant to home automation in several different ways. Safety has already been a primary concern for the elderly who live alone at home. The proposed system would enable the recognition of fall-prone elderly whose dynamic stability has been detected below a certain safety threshold. Remote health care facilities could thus be notified. The users themselves could also be alerted to increase their stability by taking steps like avoiding potentially unsafe walking surfaces. Besides the safety aspect, the e-textile pants itself would be an ideal medium for attaching multiple sensors, which enhances the context awareness capability of the existing home automation system through functions like location and motion activity level detection.



It may be argued whether the e-textile system used in the current study is economically practical. As a proof-of-concept study, however, the current research provided important information regarding the number and the site of the sensors. Attaching accelerometers at ankle and hip joints was shown to be an effective sensor configuration. The current e-textile system can be easily tailored in the future to satisfy practical needs of fall risk assessment.

In summary, the current study established the effectiveness of utilizing local dynamic stability in differentiating motion-impaired elderly from healthy individuals and demonstrated the feasibility of assessing local dynamic stability utilizing an e-textile pants system.

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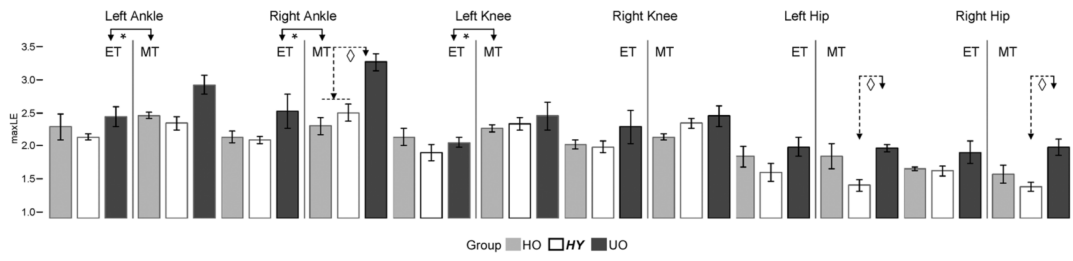
## References

1. Center for Disease Control. CDC Facts Book, 2000/2001. 2000.
2. Guimaraes RM, Isaacs B. Characteristics of the gait in old people who fall. *Int Rehab Med* 1980;2:177–180.
3. Imms FJ, Edholm OG. Assessment of gait and mobility in the elderly. *Age Ageing* 1979;8:261–267. [PubMed: 517321]
4. Dingwell JB, Cusumano JP. Nonlinear time series analysis of normal and pathological human walking. *Chaos* Dec;2000 10:848–863. [PubMed: 12779434]
5. Dingwell JB, Cusumano JP, Cavanagh PR, Sternad D. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *J Biomech Eng* Feb;2001 123:27–32. [PubMed: 11277298]
6. Scanaill CN, Carew S, Barralon P, Noury N, Lyons D, Lyons GM. A review of approaches to mobility telemonitoring of the elderly in their living environment. *Ann Biomed Eng* Apr;2006 34:547–563. [PubMed: 16550450]
7. Park S, Jayaraman S. Enhancing the quality of life through wearable technology. *IEEE Eng Med Biol Mag* May;2003 22(3):41–48. [PubMed: 12845818]
8. Nyan MN, Francis EHT, Manimaran M, Seah KHW. Garment-based detection of falls and activities of daily living using 3-axis MEMS accelerometer. *J Phys Conf Ser* 2006;34:1059.
9. Asada HH, Shaltis P, Reisner A, Rhee S, Hutchinson RC. Mobile monitoring with wearable photoplethysmographic biosensors. *IEEE Eng Med Biol Mag* May;2003 22(3):28–40. [PubMed: 12845817]
10. Bourke AK, O'Brien JV, Lyons GM. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait Posture*. to be published.
11. Nyan MN, Tay FEH, Tan AWY, Seah KHW. Distinguishing fall activities from normal activities by angular rate characteristics and high-speed camera characterization. *Med Eng Phys* Oct;2006 28:842–849. [PubMed: 16406739]
12. Giansanti D. Investigation of fall-risk using a wearable device with accelerometers and rate gyroscopes. *Physiol Meas* Nov;2006 27:1081–1090. [PubMed: 17028403]
13. Moe-Nilssen R, Helbostad JL. Interstride trunk acceleration variability but not step width variability can differentiate between fit and frail older adults. *Gait Posture* 2005;21:164–170. [PubMed: 15639395]
14. Lehn D, Neely C, Schoonover K, Martin T, Jones M. E-TAGs: E-Textile attached gadgets. *Commun Networks Distrib Syst: Model Simul*. 2004
15. Atmel Corp. AVR 8-Bit RISC Products. 2004.

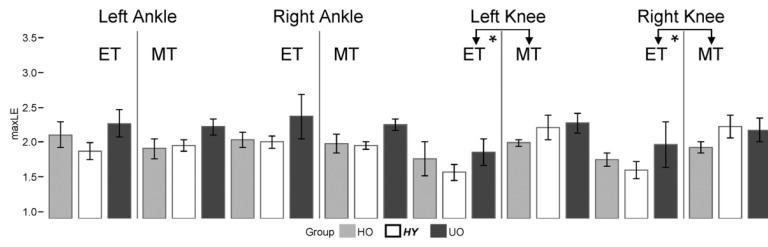
16. Analog Devices, Inc. ADXL 203 Dual-Axis Accelerometer. 2004.
17. Analog Devices, Inc. ADXRS300 Angular Rate Sensor. 2004.
18. Measurement Specialties, Inc. LDT-052K Piezoelectric Film Sensor. 2004.
19. Antonsson EK, Mann RW. The frequency content of gait. *J Biomech* 1985;18(1):39–47. [PubMed: 3980487]
20. Packard NH, Crutchfield JP, Farmer JD, Shaw RS. Geometry from a time-series. *Phys Rev Lett* 1980;45:712–716.
21. Cao LY. Practical method for determining the minimum embedding dimension of a scalar time series. *Phys D* Dec 1;1997 110:43–50.
22. Abarbanel HDI, Kennel MB. Local false nearest neighbors and dynamic dimensions from observed chaotic data. *Phys Rev E* May;1993 47:3057–3068.
23. Rosenstein MT, Collins JJ, DeLuca CJ. A practical method for calculating largest lyapunov exponents from small data sets. *Phys D* May 15;1993 65:117–134.
24. Liu, J.; Lockhart, TE. Initial biomechanical responses of unperturbed foot after slip initiation. *Proc. HFES 50th Annu. Meeting; San Francisco, CA. 2006.*
25. Liu J, Lockhart TE. Aging effect on successful reactive-recovery from unexpected slips: A 3D lower extremity joint moment analysis. *Gait Posture*. to be published.
26. Merkwirth, C.; Parlitz, U.; Wedekind, I.; Lauterborn, W. TSTool. 1.11. 1997.
27. Edmison J, Jones M, Lockhart TE, Martin T. An e-textile system for motion analysis. *Stud Health Technol Inform* 2004;108:292–301. [PubMed: 15718659]
28. Hurmuzlu Y, Basdogan C. On the measurement of dynamic stability of human locomotion. *J Biomech Eng* Feb;1994 116:30–36. [PubMed: 8189711]
29. England SA, Granata KP. The influence of gait speed on local dynamic stability of walking. *Gait Posture* Feb;2007 25:172–178. [PubMed: 16621565]
30. Abarbanel, HDI. *Analysis of Observed Chaotic Data*. New York: Springer; 1996.
31. Stergiou, N.; Buzzi, UH.; Kurz, MJ.; Heidel, J. Nonlinear tools in human movement. In: Stergiou, N., editor. *Innovative Analyses of Human Movement: Analytical Tools For Human Movement Research*. Champaign, IL: Human Kinetics; 2004. p. 63-90.
32. Williamson R, Andrews BJ. Gait event detection for FES using accelerometers and supervised machine learning. *IEEE Trans Rehab Eng* Sep;2000 8:312–319.
33. Pappas IPI, Popovic MR, Keller T, Dietz V, Morari M. A reliable gait phase detection system. *IEEE Trans Neural Syst Rehab Eng* Jun;2001 9(2):113–125.
34. Korhonen I, Parkka J, Van Gils M. Health monitoring in the home of the future. *IEEE Eng Med Biol Mag* May;2003 22(3):66–73. [PubMed: 12845821]



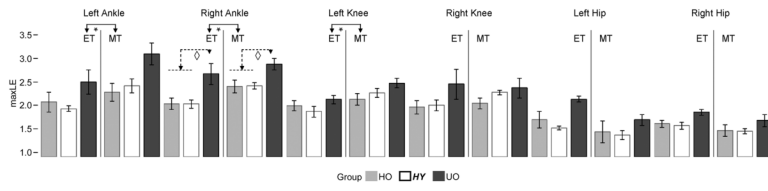
**Fig. 1.** Illustration of e-textile pants. (Only pants were used in the current study.)



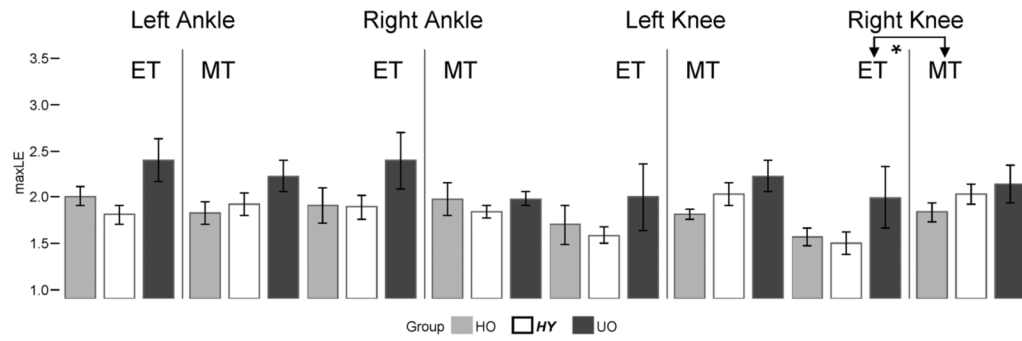
**Fig. 2.** Vertical acceleration based maxLE at speed condition 1 (100% of normal speed). \* Indicates significant system effect. ◇ Indicates significant group effect.



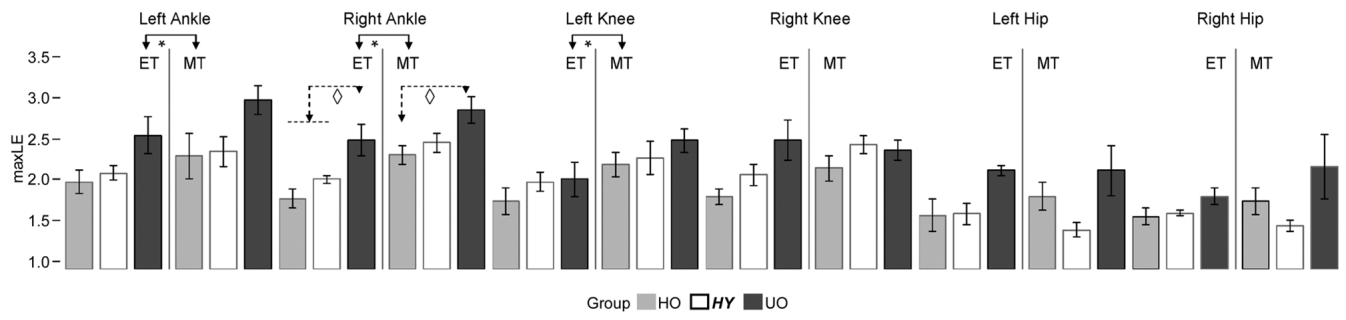
**Fig. 3.** Angular velocity based maxLE at speed condition 1 (100% normal speed). \* Indicate significant system effect.



**Fig. 4.** Vertical acceleration based maxLE at speed condition 2 (110% of normal speed). \* Indicates significant system effect. ◇; Indicates significant group effect.

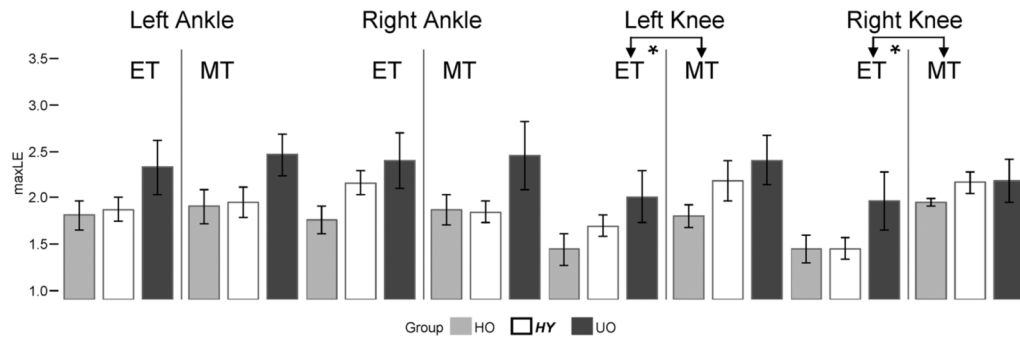


**Fig. 5.** Angular velocity based maxLE at speed condition 2 (110% of normal speed). \* Indicates significant system effect.



**Fig. 6.** Vertical acceleration based maxLE at speed condition 3 (120% of normal speed). \* Indicates significant system effect. ◇ Indicates significant group effect.





**Fig. 7.** Angular velocity based maxLE at speed condition 3 (120% of normal speed). \* Indicates significant system effect.

**TABLE I**

## Participants' Anthropometric Information

Group	Age (years)	Weight (kg)	Height (cm)
HY*	26.4 (2.3)**	71.0 (13.6)	176.8 (7.4)
HO	71.3 (6.5)	71.2 (7.3)	164.7 (9.3)
UO	71.0 (3.0)	88.6 (10.4)	172.3 (10.8)

\* HY = healthy young; HO = healthy elderly; UO = motion impaired old.

\*\* mean (std.).