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Portable, Non-Invasive Fall Risk Assessment in End Stage Renal Disease Patients on Hemodialysis

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Abstract

Patients with end stage renal diseases (ESRD) on hemodialysis (HD) have high morbidity and mortality due to multiple causes, one of which is dramatically higher fall rates than the general population. The mobility mechanisms that contribute to falls in this population must be understood if adequate interventions for fall prevention are to be achieved. This study utilizes emerging non-invasive, portable gait, posture, strength, and stability assessment technologies to extract various mobility parameters that research has shown to be predictive of fall risk in the general population. As part of an ongoing human subjects study, mobility measures such as postural and locomotion profiles were obtained from five (5) ESRD patients undergoing HD treatments. To assess the effects of post-HD-fatigue on fall risk, both the pre- and post-HD measurements were obtained. Additionally, the effects of inter-HD periods (two days vs. three days) were investigated using the non-invasive, wireless, body-worn motion capture technology and novel signal processing algorithms. The results indicated that HD treatment influenced strength and mobility (i.e., weaker and slower after the dialysis, increasing the susceptibility to falls while returning home) and inter-dialysis period influenced pre-HD profiles (increasing the susceptibility to falls before they come in for a HD treatment). Methodology for early detection of increased fall risk – *before* a fall event occurs – using the portable mobility assessment technology for out-patient monitoring is further explored, including targeting interventions to identified individuals for fall prevention.

General Terms

Algorithms; Measurement; Experimentation; Human Factors

1. INTRODUCTION

The incidence and prevalence of chronic kidney disease (CKD) is increasing worldwide and especially in the United States where it has reached what can be considered as epidemic proportions [6]. Patients with end stage renal diseases (ESRD) requiring hemodialysis (HD), especially the elderly, are growing in numbers and are more prone to negative outcomes than the general population. In spite of the multiple efforts aiming to decrease the high mortality and improve the quality of life in patients with ESRD, limited success has been achieved. Identifying other modifiable risk factors may prove to be helpful in improving the outcomes of these patients.

In particular, the increased fall rates of ESRD patients on HD is one such risk factor that, if addressed, could dramatically decrease morbidity and mortality in this population. Falls are associated with numerous physical and psychological morbidities, decreased quality of life, increased mortality, and high healthcare costs. While reducing fall accidents experienced by all older adults is a major public health challenge, it is especially crucial for ESRD patients on HD, as the fall rates are higher and the outcomes are worse for these patients than for the general population.

Fall rates have been found to be much higher in HD patients when compared to the general elderly population. In a study by Desmet and his group, the incidence of falls in HD patients was found to be 1.18 falls/patient-year, in comparison to the people living in community who have incidence of falls ranging from 0.32–0.70 falls/person-year [7]. Another group has reported fall incidence in HD patients as 1.60 falls/person-year [5]. Moreover, falls among the HD patients were more common after dialysis (73%) than before dialysis (27%) on dialysis days [5].

Identifying patients who are at higher risk of falls offers an opportunity to intervene early to help prevent fall events from occurring, thus improving patients' quality of life, increasing survival, and cutting the staggering costs associated with falls and fall-related complications. Monitoring of incidence and assessing predictors and outcomes of falls are important, as falls can be a preventable problem. The U.S. Public Health Service has estimated that two-thirds of deaths due to falls are potentially preventable [1], as multidisciplinary intervention in non-renal patients was shown to decrease the incidence of falls [39]. Thus, considering the morbidity and mortality associated with falls in HD patients, early prediction with consequent intervention to minimize risk of falls could be lifesaving and quality of life preserving for these patients.

Patients with ESRD on HD not only share the characteristics of the non-dialyzed elderly population that predispose them to fall, but also have additional risk factors peculiar to ESRD and/or HD, such as dialysis related hypotension, chronic kidney disease-mineral and bone disorder (CKD-MBD), myopathy, anemia, metabolic acidosis, dialysis disequilibrium syndrome, dialysis encephalopathy, catheter related infection/sepsis, dialysis related arrhythmias and post-dialysis fatigue. How these additional risk factors that are unique to the ESRD patients on HD contribute to the increased incidence of falls noted in this population is unclear. Understanding the mechanisms that lead to the increased incidence of falls in this population is crucial in tailoring an intervention. While significant research has identified mobility parameters that correlate with fall risk in the general elderly population (which has led to the development of a number of effective interventions), little attention has been directed towards understanding the mobility mechanisms that contribute to the increased fall rate experienced by ESRD patients on HD and whether or not those mechanisms are primary or secondary to myopathy, osteodystrophy, diabetic neuropathy, etc.

Assessing fall risk in ESRD patients on HD is crucial because the cost and invasiveness of many interventions make it impractical and undesirable to target all members of this high fall risk population. Instead, interventions must be targeted to high fall risk individuals. This requires an ability to evaluate fall risk on a patient-by-patient basis *before* fall events occur, a process which itself can be quite costly and invasive. Currently, in order to assess fall risk (i.e., degraded function and mobility), researchers and physicians often rely on assessments of a patient's motion, such as the gait of an individual with high falling rates, the tremor of a

Parkinson's Disease patient, or the motion of an individual performing activities of daily living (ADLs). However, current motion assessment techniques are invasive, qualitative, imprecise, and even inaccurate. Patient self-reports, family member observations, and professionally administered motion tests are the most pervasive methods of assessment, but they lack sensitivity and objectivity, requiring human input and invasion for short, focused periods of time, often resulting in data inaccuracies. While modern motion capture laboratories (e.g., gait labs) provide precise quantitative data, this method is cumbersome, especially for patients with ESRD already burdened with the need to go to a dialysis unit three times per week for HD treatments.

This paper details an ongoing interdisciplinary research project (combining expertise from nephrology (Abdel-Rahman), gait analysis (Lockhart), and body sensor networks (Lach)) exploring the use of wearable wireless sensor technology for fall risk assessment in ESRD patients on HD. This approach allows a patient's mobility parameters to be measured outside the laboratory setting and enables these analyses to move from being primarily a research tool to a monitoring and diagnostic tool that will allow longitudinal tracking of gait and posture to identify/predict fall prone individuals, as well as tailor the intervention to the specific defect identified and assess the success of the intervention. This will pave the way for positively impacting the longevity and quality of life of patients with ESRD on HD.

Early results from an ongoing human subjects study from five (5) ESRD patients on HD reveal that HD treatment influenced strength and mobility (weaker and slower after the dialysis, increasing the susceptibility to falls while returning home) and inter-dialysis period influenced pre-HD profiles (increasing the susceptibility to falls before they come in for a HD treatment). These results motivate a planned follow-up study in which wireless body sensors will be worn by subjects not only in the clinic immediately pre- and post-HD but also in their natural living environments for 22 hours post-HD. The ultimate goal of this project is to fill the knowledge gap about how mobility changes cause falls in this population and to develop a methodology for early prediction – and ultimately prevention – of falls.

The rest of the paper is organized as follows. Section 2 describes why patients on HD fall more often than their healthy counterparts. Section 3 describes gait analysis techniques that can be utilized to assess fall risk in HD patients and how the appropriate gait measures can be obtained using portable, non-invasive methods. Section 4 describes the experimental approach, including descriptions of the human subject data collection procedure and the data analysis methods. Section 5 presents the results, and Section 6 provides discussion and describes ongoing and future research opportunities for fall prevention in ESRD patients on HD.

2. HEMODIALYSIS AND FALLS

A review of literature on fall accidents reveals that there are multiple mechanisms involved. Factors intrinsic and extrinsic to the individual, and the hazards and demands of the environment, contribute to most falls in varying degrees. In general, the ability to walk safely and preserve balance (keeping the body's center-of-mass (COM) over its base of support) in the event of a postural perturbation (i.e., slips, trips, etc.) is dependent upon intact sensory and musculoskeletal systems. However, with post HD muscular fatigue, a variety of physiologic changes affecting these systems may interfere with gait and balance, placing these individuals at a higher risk for fall accidents.

About one half of the population undergoing HD reported post dialysis muscle fatigue (PDF) [36][23]. Fatigue has been reported to have begun with inception of dialysis and followed most treatments. These patients cite more frequently muscle fatigue than cardiopulmonary limitations as the reason for terminating maximal exercise testing [25].

Although all HD patients are exposed to similar reductions in extracellular fluid osmolarity, rapid hydraulic and molecular flux have been found to have a greater role in pathogenesis of PDF than psychological stress and blood-membrane interactions [35]. Johansen and coworkers found that HD patients demonstrated 3-fold greater muscle fatigue than controls despite the performance of less work by about one-half of the dialysis subjects and have provided evidence of central activation failure but no change in peripheral activation [18]. This excess fatigue has been considered in part due to poor oxidative metabolism and greater accumulation of metabolic by-products in the patients, with additional contribution from central activation failure. Metabolic instability had also been observed in HD patients after exercise [18]. Three-fold greater muscle fatigue in dorsiflexor muscles of HD patients may be considered as a fall risk factor, as dorsiflexor muscles play an important role in locomotion, posture, balance and prevention of falls in older adults [18]. And localized muscle fatigue of lower extremity muscles increases the fall and slip propensity [30].

Research has shown that fatigue is significantly greater in dialysis patients compared with control subjects [18]. Furthermore, a muscle's rate of recovery from fatigue depends on several factors, including duration of a task, the intensity of a task, and the physical fitness of an individual [25]. Dialysis subjects demonstrated delayed recovery of maximum voluntary contraction (MVC) force, returning to only 85% of pre-exercise MVC after 10 minutes of rest [18]. In this light, whereas acute muscle fatigue may only limit performance during vigorous activities in healthy individuals, HD patients must use their muscles at levels closer to their maximum capacity during activities of daily living. Furthermore, timing of falls in ESRD patients on HD suggests a significant increase in fall rate within the 22 hours of HD therapy [7]. As such, continual monitoring of mobility characteristics associated with post HD is required to ascertain mechanisms associated with fall severity among this cohort.

The UVA Division of Nephrology performed a pilot study on 76 HD patients [2]. Baseline assessments followed by documentation of falls prospectively during a one year period were carried-out using standardized protocols. Patients were followed-up for an additional two years and four outcomes were recorded: all-cause death, admission to nursing home, and the number and duration of all hospitalizations. We found that 26.3% fell over a 12 month period. Females had a much higher risk of falls than males (odds ratio = 4.64, $p = 0.006$). The number of falls was significantly higher in the elderly group (age ≥65 years) (38.2% vs. 16.7%, $p=0.034$). During the two-year follow-up, compared to non-fallers, fallers had a 2.13-fold increase in risk of death, a nearly 2-fold increase in number and duration of hospitalizations, and a 3.5-fold increase in risk of nursing home admission (Figure 1). These poor outcomes were even more acute in the recurrent fallers.

3. GAIT ANALYSIS

3.1 Gait Characteristics and Falls

The acquisition of gait characteristics during walking provides important information about limb propulsion and control [40] and provides insight into muscle performance. Furthermore, gait evaluations can be used as global indicators of stability. Together, gait analyses provide an effective tool for evaluating and quantifying gait problems associated with fall-prone individuals. Most studies using gait analysis have relied on comparisons of a limited number of specific gait characteristics (e.g., step length and step frequency, etc.) by normalizing and averaging together data from a number of isolated and independent strides. This approach ignores the high degree of correlation that exists between various aspects of an individual's gait and is not well-suited to address the fundamental control task of locomotion (i.e., maintaining dynamic stability). As such, to accurately evaluate the extent of gait deviations from normal gait, it is necessary to consider not only how a single stride is generated, but also how movements are controlled from one stride to the next [40][9], thus requiring continuous monitoring of gait.

Age- and disease-related 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. For example, a study investigating the gait characteristics of older adults who were hospitalized after falls [10] suggested that individuals with step variability fell more often than non-fallers. Furthermore, the work of Imms and Edholm [15] also demonstrated that gait variability is linked to falls in the elderly.

While variability (linear) is often equated with stability, the foundation for this assumption is lacking. In essence, traditional linear tools can mask the true structure of motor variability. Gait characteristics are usually assessed from a few strides which are then averaged to generate a mean ensemble curve. The objective of a mean ensemble curve is to define an "average" picture of the subject's gait. However, this averaging procedure is frequently accompanied by time normalization which tends to pull or stretch the original data. As a result, the temporal variations of the gait pattern are lost. Furthermore, linear measures such as standard deviations only quantify the average differences between strides, independent of the temporal order in which strides occur. As such, these linear measures, although effective, contain limited information about how the locomotor control system responds to perturbations either within or across strides (i.e., motor control) [8][4]. Thus, understanding the locomotor control can help predict future falls since motor variability could arise due to failure of the automatic stepping mechanisms.

A local dynamic stability measure, which is based on nonlinear dynamic theory, has been proposed as a more precise measurement of individuals' resistance to perturbations. Using the dynamic stability concept, Dingwell and Cusumano [8] successfully showed that individuals with pathological gait exhibited a slow-down adaptation to increase their stability, and clearly demonstrated the difference 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 (treadmill gait and over-ground gait), identify group differences in locomotor stability between post-polio patients and age-matched controls, and patients with and without peripheral neuropathy [14]. Recently, Lockhart and Liu [24] used similar measures to differentiate fall-prone elderly from healthy young and healthy older adults. This suggests that similar dynamic analyses may be applied to quantify stability differences associated with HD-related gait adaptations and to differentiate fall-prone ESRD patients.

As noted earlier, exposure to fall hazards is a nearly constant reality for HD patients. As such, the accident statistics presented in Section 2 may remain unchanged unless substantial progress is made towards new means of reducing fall occurrences in this population. Such reductions are typically achieved through either fall protection (for fall to a lower level) or fall prevention. Fall protection refers to interventions aimed at minimizing injury severity after a fall event is initiated. The current standard for fall protection and other existing standards address this issue, covering fall protection systems, guardrails, personal protective equipments and other related approaches. Despite the existence of such standards, such protection systems are not currently used with sufficient frequency or correctness. Furthermore, fall protection cannot prevent an incident from occurring [37]. Given this evidence, reliance on fall protection may not be an effective approach towards minimizing HD-related fall accidents.

Rather, fall *prevention* remains an important and perhaps even a critical task. As such, there is an important need for methods to evaluate existing and develop new prevention strategies, and more generally to determine factors that lead to HD-related fall accidents. As most age- and HD-related falls appear to be initiated by post-HD session fatigue, fall prevention can be facilitated by a better understanding of gait and posture during and after the HD sessions, factors that adversely affect fall initiation and recovery (fatigue and aging), and interventions that promote safe walking.

3.2 Current Methods

Kinematic analysis measures the geometry of movement patterns without considering the forces that cause the movement. The majority of kinematic evaluations associated with gait and mobility analyses are performed using videographic or optoelectronic systems integrated with hardware and software systems. Both of these systems involve marker application to the subject, setting up and calibrating the reference frame, video or marker recording, digitization, transformation, smoothing and normalization. With currently available technology, digitization alone requires about 30 minutes for each five seconds of captured data. Furthermore, preparation for the test, such as attaching a complete set of retro-reflectors for the motion capture system is a lengthy process, requiring approximately 30 minutes for a healthy young adult; more time may be required for an elderly HD patient. The amount of time required and the complexity of the equipment make this an expensive process, and use of these systems is usually confined to the laboratory due to the need for a hard-wired connection to the subject and/or controlled lighting conditions. It is therefore impractical and undesirable to require all ESRD patients on HD to regularly go to a gait lab for such an assessment, especially since this population is already burdened with multi-hour HD sessions up to three times per week.

Various other types of motion sensors have also been developed in an attempt to assess gait and mobility characteristics in the field. These include pedometers and simple accelerometer-based systems. The advantage of these systems is that the device is small (allowing a subject to wear the monitor for long periods of time without interfering with normal movement) and has the ability to store data continuously over long periods of time. This information can then be analyzed to examine patterns of activity over the course of several days or weeks. More recently, several investigators have used accelerometers to study the dynamic stability and kinematics of human gait. Yack and Berger [41] studied the ratio of the even-to-odd harmonics of the accelerations (Fourier analysis) recorded at the second thoracic vertebra by a tri-axial accelerometer. The ratio of summed amplitudes of the even and odd harmonics was calculated for each stride and averaged across ten strides. This ratio was related to the smoothness of the gait (a larger harmonic ratio reflected a smoother gait pattern), and unsteady older adults exhibited a lower ratio.

A few teams [21][29] have used accelerometers to study balance while standing quietly. Kamen et al., [21] used two uniaxial accelerometers taped to the back (S2 level) and forehead of the subject and measured in the anterior-posterior (A/P) direction. They calculated root mean square (RMS) and frequency spectrum of the signals and performance parameters. Unfortunately, this sensor configuration is affected by the acceleration of gravity, a function of the angle of the accelerometer with respect to the vertical. Moe-Nilssen [29] used triaxial accelerometers to quantify balance during human walking. The average tilt of the sensor was used to subtract the static gravity error and then the data were transformed to a horizontal-vertical orthogonal coordinate system by a trigonometric algorithm. RMS was used on the data from each of the three axes as a performance parameter. This system has demonstrated test-retest reliability. Mayagoitia et al. [27] recently presented a triaxial accelerometer-based system for determining the ability to maintain balance while standing by approximating the level of the center of mass. Their results suggested that the accelerometer measurements were sensitive enough to be able to distinguish between the different balance conditions using the force platforms.

Although short-term laboratory experimental sessions can measure gait characteristics by directly measuring gait variables, intermittent activity in a field setting is much more difficult to assess. In that regard, accelerometry has several advantages over traditional laboratory-based systems for gait analysis, primarily that it provides data over an extended period of time. For example, Kaufman et al., [22] analyzed pathological gait and found that at least seven gait cycles are needed to obtain temporal data, but the results lacked precision. They actually needed 22 gait cycles to obtain precise temporal data. This long temporal recording could explain the good reproducibility (between and within testers) in their results. As such, the accurate prediction depends on the usability and the capability of the instrumentation. Improved routine analysis of locomotion and posture depends on the development of new tools. Any longitudinal gait analysis system must not introduce any artificial stimulus, and the ideal system should encumber the subject minimally [1].

3.3 Portable, Non-Invasive Gait Measurement

While the accelerometer-based studies mentioned above provide more portability than a gait laboratory, existing systems are too large or otherwise cumbersome (e.g., most are wired) to wear continuously over an extended period of time, as is required of HD patients in this study. The more portable and non-invasive devices on the market (from the ActiGraph and Actiwatch to the Fitbit and simple pedometers) do not provide the more precise measures of gait and posture required for this study.

Therefore, the TEMPO (Technology-Enabled Medical Precision Observation) platform is being used in this project. TEMPO (shown in Figure 2) is a wireless body sensor network platform developed by the INERTIA Lab at UVA that provides precise human motion and orientation data continuously and non-invasively in any location over an extended period of time [3]. TEMPO supports any number of wireless sensors nodes that can be placed at arbitrary points of interest on the human body. Sensors capture three axes of both linear acceleration and angular rate at 120 Hz, providing six degrees of freedom motion capture in the form factor of a wristwatch. All of this data is then transmitted over a Bluetooth wireless channel to an aggregator somewhere in the room. TEMPO has been deployed in a number of medical research studies, including assessing tremor in Parkinson’s disease and essential tremor patients [13][33] and agitation and akathisia in dementia patients [11]. These studies were enabled by this technology, as they all depend on continuous and precise motion data capture and analysis.

In this study, TEMPO is used to continuously and non-invasively collect gait and posture data, which can then be analyzed to study the fall risk mechanisms in ESRD patients on HD and ultimately identify high fall risk patients in this population. TEMPO has previously been used to study the relationship between gait disorders and fall risk. In particular, TEMPO has been used to classify a “shuffle” gait (Figure 3), which research has shown to be a prominent cause of falls in the elderly. Such classification, however, presents a formidable challenge due to the natural variability of gait both within and between individuals. This variability complicates the processes preceding classification, such as feature identification, selection, and extraction. Thus, robust and generalized signal and information processing methods were needed to classify inertial gait data both on- and off-node. Using data collected on subjects with a TEMPO node on the right ankle, shuffle gait classification was performed using information-theoretic feature extraction and neural networks. This approach yielded near 98% accuracy of classifying normal from shuffle gait using as few as two features from a gait cycle and one measurement location (i.e. ankle) as training and test vectors [12].

4. METHODS

4.1 Experimental Setup

Pre- and post-HD mobility measures were collected from five ESRD patients on HD over the course of five months in an out-patient facility. Participants wore five TEMPO nodes (one on each ankle, one on each wrist, and one on the sacrum) and were then asked to perform the same four tasks both before and after their HD treatment: two minutes of walking, three Get-Up & Go tests, three Postural Locomotion and Manual (PLM) control tests, and three tests of foot strength using a custom made measurement device. The subjects wore five TEMPO nodes (both wrists, both ankles, and the sacrum) for the first three tasks that were constantly transmitting six degrees of freedom movement data to a handheld computer. These tests provide the opportunity to assess mobility gait characteristics, dynamic stability, and functional assessments.

4.2 Mobility Analysis

4.2.1 Strength—ESRD patients have been found to be suffering from post HD fatigue and changes in muscle strength and neuromuscular function [17][34][36]. In order to study such dialysis induced strength variability, clinicians require an accurate, reliable method for measuring strength during the course of dialysis. We developed a torque sensor mounted leg brace that can measure ankle plantarflexion torque with good reliability. This device can provide an objective assessment of ankle plantarflexion muscle performance by measuring variability in MVC during dialysis. A low pass filter constructed in LabVIEW was designed and used to filter raw signals collected by the torque sensor (SWS-100 Transducer Techniques, USA) with its filter order, cut-off frequency, and resulting gain and phase adjusted accordingly.

Patients can don the device during dialysis treatment and exert maximum voluntary torque for 5 seconds (Figure 4). A break of three minutes between measurements ensured complete recovery from fatigue due to ankle force exertion.

4.2.2 Posturo-Locomotion-Manual (Simultaneous Index SI)—The Posturo-Locomotion-Manual (PLM) test was developed for assessment of the movement capacity of patients with Parkinson’s disease [19][20][38]. The PLM test measures postural function, gait, and a goal directed reaching arm movement and the efficacy with which these movements compose a whole-person dynamic performance. This tool has been in clinical use for more than a decade to objectively assess movement capacity in patients with various diagnoses. The traditional technique for this task is optoelectronic kinesiology to quantify the performance during a simple test in which subjects pick up an object from the floor and transport it up to a shelf, thereby forcing the body through postural, locomotor and manual movements (Figure 5). However, this laboratory-based approach is facing several limitations for its prohibitively expensive and nonportable characteristics as discussed in Section 3.

In lieu of such limitations, we developed an algorithm based upon inertial measures (i.e., accelerations) to assess PLM parameters which make it possible to assess separate phase time in sequential movement by analyzing accelerations outside of the lab environment (Figure 6) [42]. The data collected were stored in ASCII files and dual-filtered in Matlab using built-in Butterworth filter functions. Phases of the PLM task consisted of picking up the object (500g) from the floor with the left hand, walking 1.5m forward starting with the right foot, placing an object briefly (i.e., stamping) at chin height, and walking back to the start line. During the PLM task, postural, locomotion and manual phase time as well as the overlap between phases can be computed, and the overlap is interpreted as the movement capacity of freely moving individuals (i.e., Simultaneous Index - SI). In other words, more overlap between phases (i.e., lower SI value) indicates better mobility [16].

4.2.3 Local Dynamic Stability—The acquisition of gait characteristics during walking provides important information about limb propulsion and control and provides insight into muscle performance (i.e., post-HD fatigue). Furthermore, gait evaluations can be used as global indicators of stability. Together, gait analyses provide an effective tool for evaluating and quantifying instability conditions associated with HD treatments.

Stability can be quantified from engineering analyses of movement kinematics. And to accurately evaluate the extent of gait deviations due to moving environment from normal gait, it is necessary to consider not only how a single stride is generated, but also of how movements are controlled from one stride to the next requiring continuous monitoring of gait. A textbook by Leipholz describes how stability of any dynamic system can be quantified from engineering analysis of the kinematic movement patterns and kinematic disturbances. These techniques have been used to identify group differences in musculoskeletal instability between post-polio patients and age matched controls. Similar analysis was applied to quantify stability limitations associated with post-HD fatigue.

Local dynamic stability was quantified by the maximum Lyapunov Exponent (maxLE) from a nonlinear dynamics approach [24]. Briefly, each experimental time series measurement (e.g., acceleration measures at right hip joint identified with heel contact dynamics as shown in Figure 7) can be reconstructed into a state space with sufficient dimensions to describe the target dynamic system unambiguously. A state space is defined by the independent coordinates (dimensions) required to describe the target dynamic motion. Though different ways can be used to construct such a state space, the most commonly used one is the so-called time-delayed coordinate method [24]. The time-delayed coordinate vector can be defined as:

$$y_n(d)=\{s(t_0+n\tau_s),\, s(t_0+n\tau_s+k\tau_s),\cdots,\, s(t_0+n\tau_s+k(d-1)\tau_s)\} \\ n=1,2,\cdots,d \qquad \text{Eq. 1}$$

where s is the original time series data, t_0 is some initial time, $\tau=k\tau_s$ is an appropriately chosen time delay, and the integer d is the embedding dimension. The two unknown parameters, time delay τ and the embedding dimension d, can be estimated by using the auto mutual information approach and nearest false neighbors approach, 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. 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 λ_{max}, can be defined as:

$$d(t)=De^{\lambda_{\max}t} \qquad \text{Eq. 2}$$

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. Regarding finite experimental time series data with noise embedded, a special algorithm dealing with discrete data sets has to be employed to estimate λmax. Taking the log of both sides, the above equation can be approximated as:

$$\ln\lfloor d_j(i)\rfloor \approx \lambda_{\max}(i\Delta t)+\ln\lfloor D_j\rfloor \quad \text{Eq. 3}$$

where $d_j(i)$ is the Euclidean distance between the jth pair of neighboring points at ith steps. The variable λ_{max} is then approximated (Figure 8).

4.2.4 Timed Get-Up & Go—The timed Get-Up & Go test is a reliable and valid analysis for quantifying functional mobility for clinical changes over time [32]. The test is quick and requires no special equipment or training, and thus can be easily included as part of the routine medical examination before and after HD treatment. Patients can be observed and timed to perform a series of maneuvers starting from sitting comfortably in a straight-backed chair, rising from the chair, standing still momentarily, walking a distance of 3 meters, turning around, walking back to the chair, turning around, and then sitting down in the chair. Undue slowness, hesitancy, abnormal movements of the trunk or upper limbs, staggering and stumbling during performing the test are further considered as indicators of possible fall risk [26]. Patients can wear TEMPO nodes while undergoing this test, and postures of sitting, standing and walking can be identified as shown in Figure 9. Furthermore overall movement time can be computed, giving the same metric currently captured by health staff watching the patient while holding a stop watch.

5. RESULTS

5.1 Strength

The results from the plantarflexion torque tests indicated that post-HD strength measure was significantly lower than the pre-HD strength measure (p=0.0032) (Figure 10). This corroborates data from studies on ESRD patient fatigue discussed in Section 2. Summary means and standard deviations of the mobility parameters are presented in Table 1.

5.2 Posturo-Locomotion-Manual (SI)

The results from the inertial PLM tests showed more overlap of movement control during pre-HD than post-HD suggesting poorer (p=0.1) mobility as measured by SI (Figure 11). Additionally, interaction between interdialysis period and pre-post HD indicated that two-day interdialysis period affected pre-HD SI measure indicating poorer mobility with two-day than the three-day interdialysis period (p=0.03) (Figure 12).

5.3 Local Dynamic Stability

Local dynamic stability was quantified by the maxLE from a nonlinear dynamics approach. The results indicated that no significant differences in dynamic stability between the pre- and post-HD sessions (Figure 13) and suggested that the problem of fall-risk in HD patients is unique when compared with other elderly individuals with high fall risk.

5.4 Timed Get-Up & Go

Significant differences were observed for the pre- and post-HD Get-Up & Go times. Post-HD time was significantly longer than the pre-HD time across the subjects (p=0.02). Since this time can be obtained using TEMPO nodes, this measure can now be taken at home over extended periods of time without another individual to watch and keep time.

6. DISCUSSION AND FUTURE WORK

This project is working to address the increased fall rates of ESRD patients on HD by using wearable wireless body sensors for continuous, portable, non-invasive mobility assessment.

Data collected with this technology enables researchers to better study the relationship between various mobility parameters and fall risk in ESRD patients on HD and empowers clinicians to identify high fall risk patients in this population and to better target fall risk reducing interventions.

In this study, we used the TEMPO system to capture mobility parameters immediately pre- and post-HD to determine effects associated with HD sessions and interdialysis periods and to ascertain the effects of post-HD fatigue. The results suggested that the problem of fall-risk in HD patients is unique when compared with other elderly populations with high fall risk. Furthermore, post-HD fatigue was evident as indicated by the MVC results.

Maximum Isometric PF strength is associated with balance control and low ankle strength is an indicator of high risk of falling [28][31]. Hemodialysis patients were found to have comparable pre-dialysis mean ankle strength (64.9±24.4Nm) to that of healthy population (68.6±22.8 Nm) [28], but mean ankle strength deteriorates by approximately 12Nm upon dialysis. This deterioration in post dialysis ankle PF strength may be due to dialysis induced alterations in neuromuscular function, thus further increasing fall risk in these individuals.

The results of this study indicate significant differences between pre and post dialysis ($p=0.02$) on overall Get-Up & Go times. This suggests that patients did not face equal difficulty with each component of the task when performing it pre- and post- dialysis. HD patients are found to be facing more difficulty in performing the Timed Get-Up & Go task as seen by increased post-HD completion times. Future studies into patient control at the component level could help identify whether they have more difficulty with turning and sitting components or with standing or walking components. This task could help us identify just the right component and specific functional deficit in post-HD patients to predict fall-risk.

We further found that patients exhibited similar local dynamic stability (maxLE 0.49–0.53) in pre- and post-HD sessions. This shows that their neuromuscular control system is intact and has the ability to attenuate disturbances manifested from either neuro-control errors or environmental noises during walking. Furthermore, this capability is retained even after dialysis treatment. A future study with more participants could further strengthen these results.

Interdialysis period also influenced the motor control and resulted in decreased motor coordination. Motor control delay coupled with lower extremity strength degradation can lead to difficulty in maintaining balance upon a perturbation. As such, care should be taken when releasing HD patients to their homes after the HD sessions.

The results from the interdialysis analysis further suggested that mobility was better after the three-day interdialysis period than two-day interdialysis period. Specifically, a mobility parameter such as SI was much lower for pre-HD sessions associated with three-day interdialysis period than two-day interdialysis period. However, this effect was mitigated by the time they received the HD treatment (i.e., post-HD session). This suggests that with three-day interdialysis period, subjects were able to recover from the post-HD fatigue and returned to their normal mobility profile, whereas, with two-day interdialysis period, residual effects of post-HD fatigue was evident. Although implicated, further study is planned with more participants and with longer data collections to elaborate on the mechanisms associated with these changes.

An important aspect of this research is to quantitatively assess the mobility deficits associated with HD sessions (i.e., immediately pre- and post-HD and continuously for 22 hours post-HD) to ascertain the prediction algorithms utilizing the fall-risk threshold levels from the literature and the repeated measures data from the followup study (i.e., delta-longitudinal comparison of individuals' mobility parameters). As such, differential effects of time-varying (pre-, immediate post-, 22hr post-, and longitudinal-HD) characteristics associated with mobility and gait must be determined to develop a fall risk prediction monitor. This method will facilitate longitudinal tracking of gait and posture to identify/predict fall prone individuals, as well as tailor the intervention to the specific deficits (e.g., strength, gait, or balance) identified and assess the success of any interventions.

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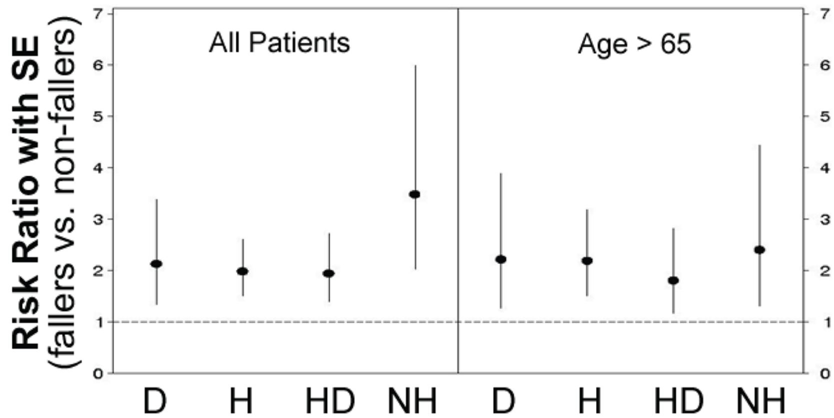

Figure 1.
Long-term outcome (risk ratio with standard error (SE)) for fallers vs. non-fallers in ESRD patients on HD. (Outcomes considered: death (D), number of hospitalizations (H), number of days in the hospital (HD), and nursing home admission (NH).)

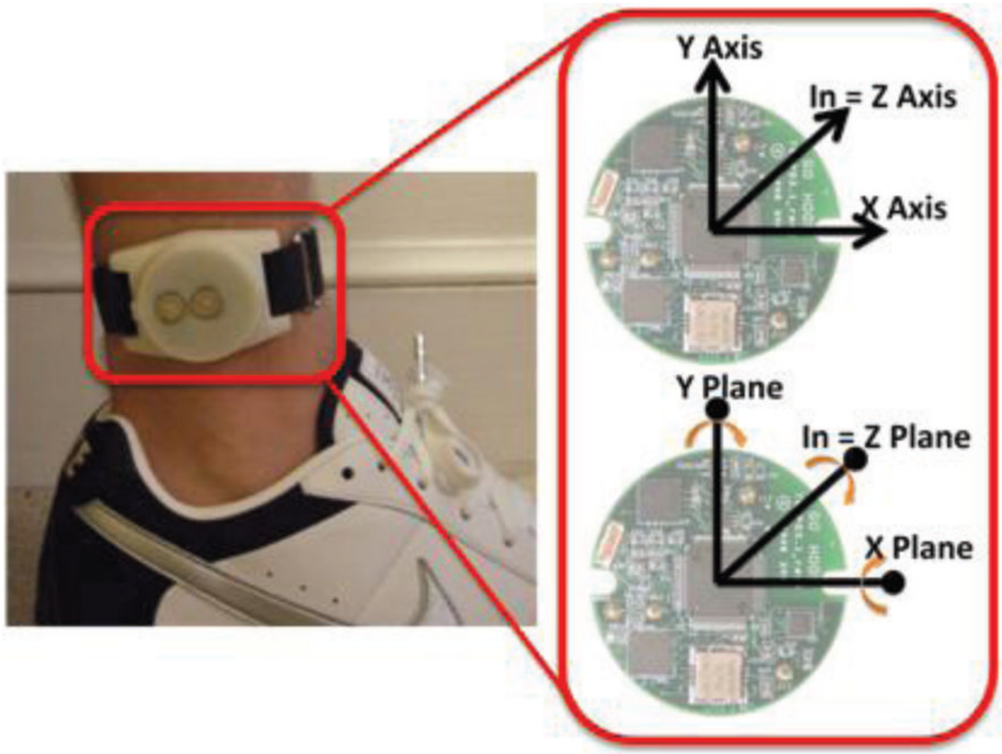

Figure 2.
TEMPO node providing wireless six degrees of freedom motion capture in a wristwatch form factor.

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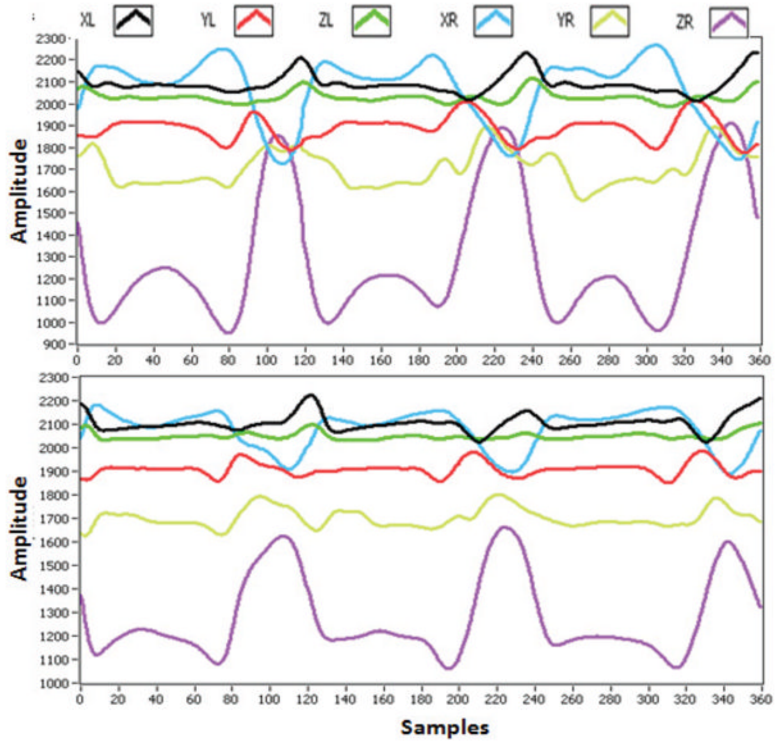


Figure 3.
Gait cycle data collected from an ankle-worn TEMPO node with normal gait (top) and shuffle gait (bottom).

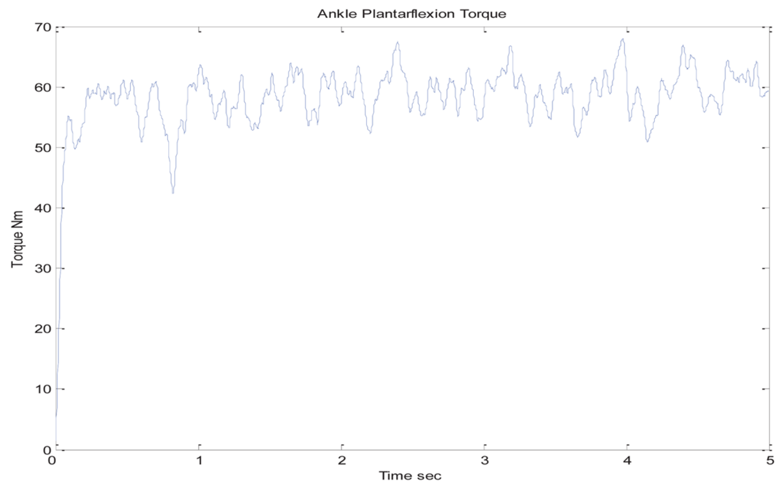


Figure 4.
Ankle plantarflexion torque collected for 5 seconds. Single strength measure was calculated as a mean of 3 second interval at which maximum torque is reached.

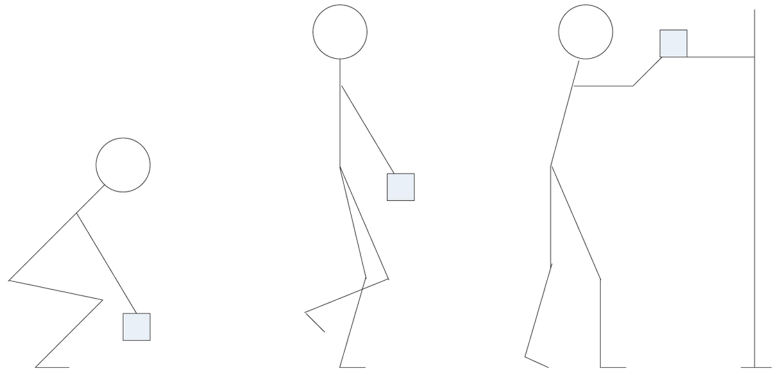
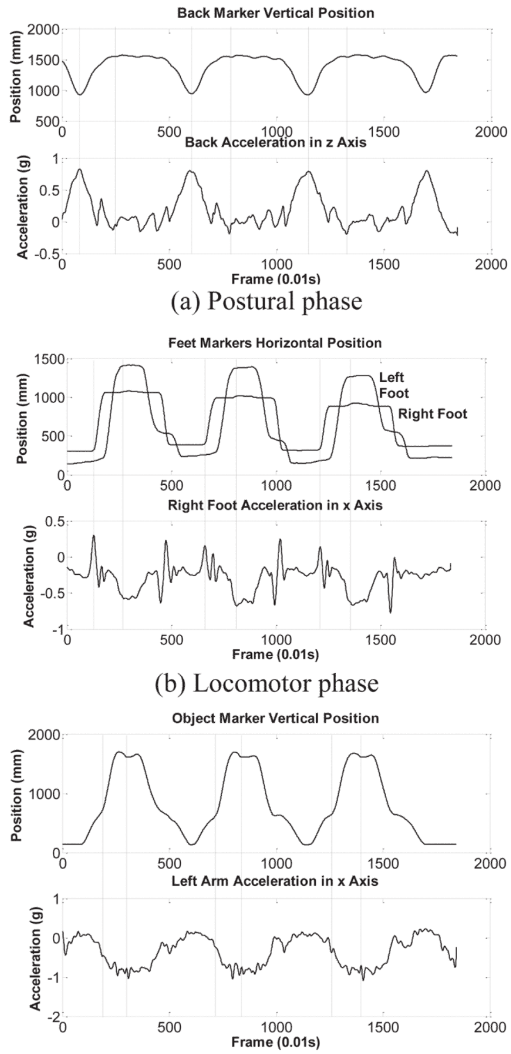


Figure 5.
Sequence of tasks in PLM test.



(a) Postural phase

(b) Locomotor phase

(c) Manual phase

Figure 6.

Patterns of the sensor data describing the time epochs associated with phases of PLM movements [42].

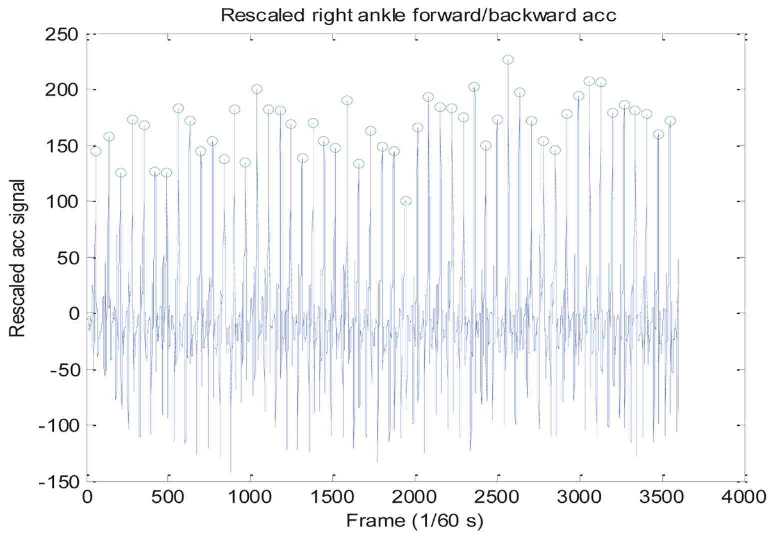


Figure 7.
Heel contact identification.

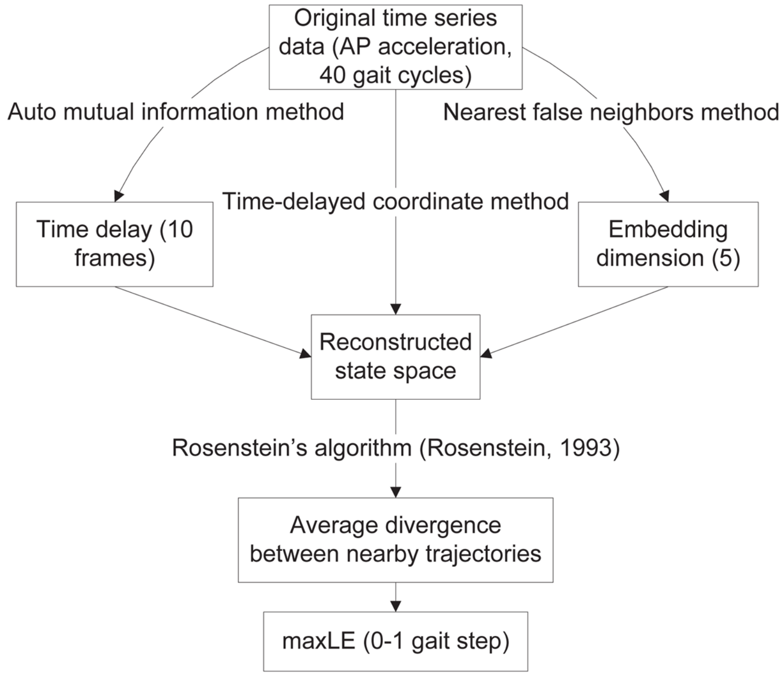


Figure 8.
Illustration of local dynamic stability computation.

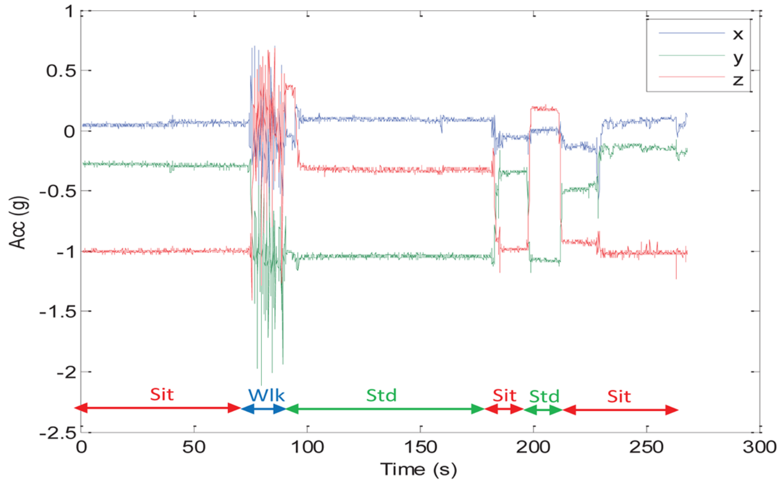


Figure 9.

Get-Up & Go analysis using TEMPO (only accelerometer data shown).

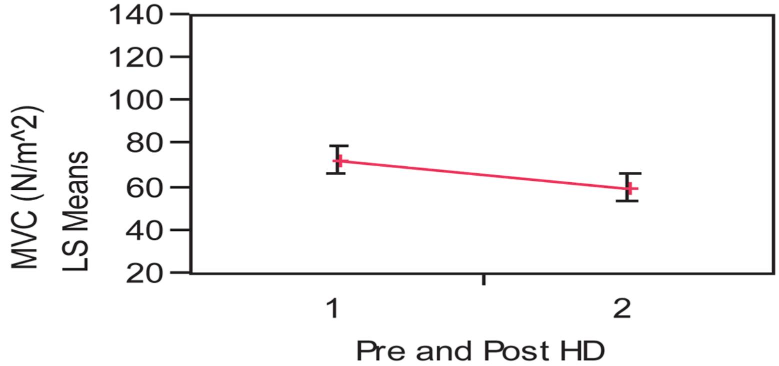


Figure 10.
Strength measure (MVC) during pre and post-HD session.

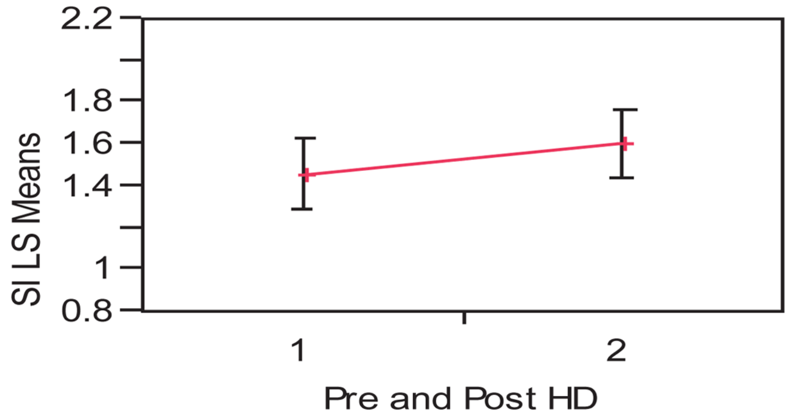


Figure 11.
SI for pre- and post-HD.

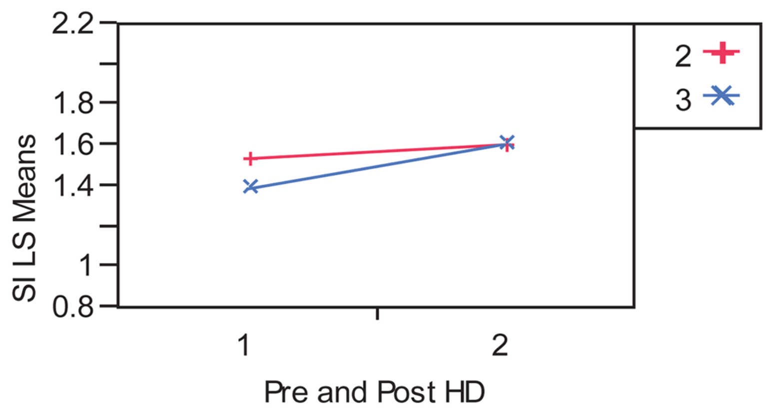


Figure 12.
SI associated with pre- and post-HD and two- and three-day interdialysis periods. Interdialysis period did not influence the post-HD measures as seen in the pre-HD measure of SI.

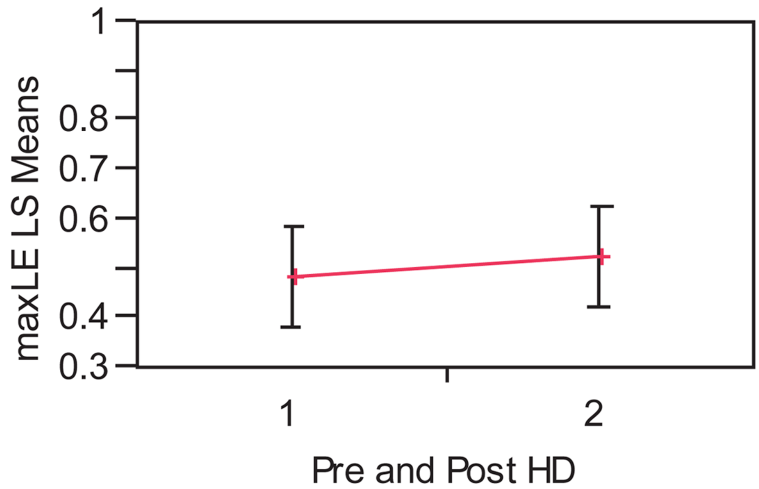


Figure 13.
Dynamic stability results of pre- and post-HD measures.

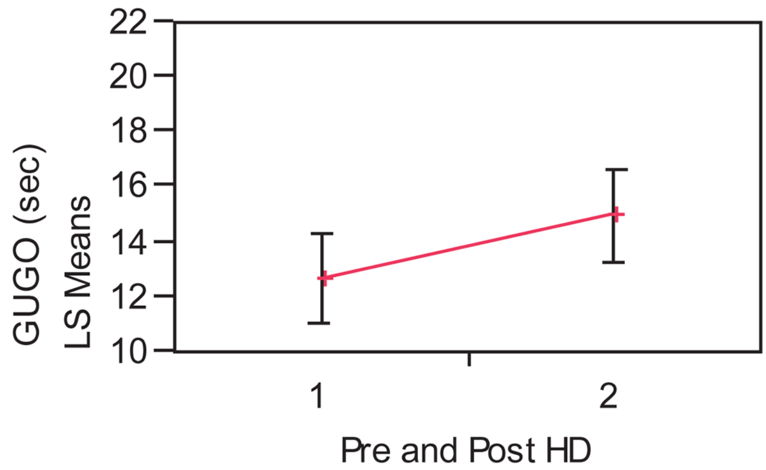


Figure 14.
Timed Get-Up & Go trial results of pre- and post-HD measures.

Table 1

Results of mobility measures during pre- and post-HD sessions and interdialysis periods

Pre/Post	Measures	Units	Mean	Standard Deviations
Pre	GUGO MT	Sec	13.0554	1.72
	Max LE	Units	0.49209	0.11
	MVC	Nm	64.9972	24.43
	SI Index	Units	1.46	0.27
Post	GUGO MT	Sec	15.47	3.14
	Max LE	Units	0.53636	0.14
	MVC	Nm	52.3362	23.91
	SI Index	units	1.57846	0.26

Interdialysis Days	Measures	Units	Mean	Standard Deviations
2 Days	GUGO MT	Sec	14.1867	2.9
	Max LE	Units	0.5202	0.14
	MVC	Nm	60.6720	28.03
	SI Index	Units	1.5655	0.28
3 Days	GUGO MT	Sec	14.4338	2.63
	Max LE	Units	0.5006	0.09
	MVC	Nm	54.1548	14.48
	SI Index	units	1.4150	0.21