THE IMPAIRMENT AND RECOVERY OF DYNAMIC WALKING STABILITY DURING VIRTUAL ENVIRONMENT EXPOSURE IN THE ELDERLY

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The emerging technology of virtual reality (VR) used in motor rehabilitation might bring in challenges to elderly users' locomotion safety. The objective of this study was to investigate such effects of virtual environment (VE) exposure to the dynamic stability of lower extremities by using a head mounted display (HMD). Twelve healthy elderly were randomly assigned with real world or VR walking conditions. Maximum Lyapunov exponents (maxLE), which served as a general measurement of dynamic stability, were assessed for real world walking, VR walking in the initial phase and VR walking in the habituated phase. Significant degradation of stability at the initial phase and remarkable recovery of stability after VE habituation were found at five lower extremity landmarks out of six, suggesting potential problems for the elderly to accept VR based interventions and the importance of habituation to a new perturbation. Meanwhile, across all walking conditions, dynamic stability was found to be increased from ankles up to hip joints. And a novel method for computing maxLE appeared to be reasonable and feasible for analyzing treadmill walking trials which were relatively short.

INTRODUCTION

The rapid development of virtual reality (VR) technology is bringing in new opportunities to motor rehabilitation. Various types of novel VR instruments such as the head mounted display (HMD) and the haptic glove have been used to provide users with simulated, but highly lifelike and well controlled virtual environment (VE) that they can interact with (Sveistrup, 2004). This merit is of great importance to the design of interventions because it offers a way to assign tasks of different difficulty to the users without having them exposed to the real risk.

Promising as the VR technology could be, the gap between the virtual environment and the real world has not been fully filled yet. One of the most crucial virtual reality induced symptoms and effects (VRISE) is motion sickness caused by the visual interface (Cobb et al., 1999; Stanney et al., 1999) since it may restrict the view and cause conflicts between visual and vestibular sensory systems.

The elderly is the major population receiving motor rehabilitation because of the greater incidence of motor prohibitive diseases (e.g. Parkinson's, stroke, hip fracture, etc.) in this population. Unfortunately, due to the general sensory degradation with ageing, they may suffer more from the VE exposure than the healthy young population. And it is possible that the negative impacts of an ill-designed VR intervention would turn out to be more significant than the positive effects. As a result, benefits and detriments of VR applications designed for the elderly have to be carefully evaluated before implementation.

As early as in the 1990's, posture and gait instability after VR immersion has brought attention of several researchers (Cobb & Nichols, 1998; Kennedy & Stanney, 1996). Temporal and spatial parameters (e.g. time to hold a posture, sway magnetometry, step completed in a heel-to-toe walking test) were measured pre and post VR immersion for comparison. Although the results varied by individual, immersion time and the specific VR instrument, evidence such as the posturographic measurements did demonstrate inducement of instability after VE exposure (Cobb, et al., 1999). And Cobb et al. further suggested that the absence of significant difference for some parameters may because of the the selection of measurements. In other words, those being studied were not the most appropriate parameters describing the underlying mechanisms of motor control and stability maintenance.

The pre and post comparison indicated the aftereffects of VE exposure to posture and gait, while the tasks in the virtual environment were not necessary to be static postures or walking. Following this, later studies examined kinematic and kinetic parameters during walking in the virtual environment (Giphart et al., 2007; Hollman et al., 2007; Hollman et al., 2006). Parameters that have been found to change significantly include step length, step width, walking speed, heel contact and toe off forces, arm and leg coordination, etc. However, a fundamental question that whether changes in these parameters are results of instability or necessary adaptations to maintain stability remains unclear. To answer this question, it becomes necessary to have a general parameter that can assess how stable a system (i.e. the whole body or a moving segment) is, regardless of the detailed changes of system elements.

Local dynamic stability, as measured by the maximum Lyapunov exponent (maxLE), is a good candidate to meet such requirements. In general, maxLE assesses how fast or how well a dynamic system recovers from a perturbation (Dingwell & Cusumano, 2000). Since VE exposure can be considered as a sensory perturbation adding to the real world walking conditions, changes in maxLE (if there's any) could represent the direct effects of VE to locomotion stability. However, to the best of the authors' knowledge, few studies have been conducted to assess maxLE during VR walking, not saying assessing the changes of stability as a function of VE exposure time.

The current study aimed at examining healthy older adults' local dynamic stability of lower extremities while walking in the virtual environment. Since gait adaptation may occur with time, maxLE was assessed both at the initial phase and the habituated phase of VE exposure, and was compared to the real world walking. Specific objectives included: 1) to inspect the effects of initial virtual environment exposure to locomotion stability; and 2) to investigate the effects of learning and adaptation on locomotion stability after habituated to the virtual environment.

METHOD

Subjects

Twelve healthy elderly from a university community were recruited in the study. They were found to have no significant difference in functional status by a general health examination. None of them had VE exposure experience previously. Subjects were randomly assigned into the real world walking (RW) group and the virtual reality walking (VR) group. After the assignment, preliminary statistical analysis was conducted to make sure that there was no significant difference in age, walking speed (WS) and step length (SL) between the two groups (Table 1).

Table 1: Subject's demographic information, data adapted from our previous study (Liu et al., 2008).

Group	Age	WS (m/s)	SL (m)
RW	73.5±4.4	1.21±0.17	0.67±0.07
VR	73.8±5.8	1.22±0.07	0.66±0.04

Apparatus

Six retro-reflective markers were attached on the subject's ankles (at lateral malleolus, LA and RA), knees (at lateral condyle, LK and RK) and hip joints (at ASIS, LH and RH). A six-camera optoelectronic motion capture system (ProReflex, Qualysis Medical AB, Gothenburg, Sweden; 100Hz) recorded the subject's 3D kinematic data during walking.

A head mounted display (Glasstron LDI–100B, Sony, Tokyo, Japan) providing a 3D dynamic view of a downtown street (Figure 1) was used by the VR group. The evolvement of the street view was synchronized with the subject's walking speed so that the subject would feel like walking in the virtual street.

Figure 1: A snapshot of the street view in the HMD

Subjects were provided with standard laboratory clothing including a sleeveless shirt, shorts and a pair of athletic shoes to minimize the possible interference of the clothing to marker tracking.

Experiments

Written consent was first obtained from each subject prior to any data collection. Next, subjects were instructed to try and get familiar to the laboratory treadmill until they could walk on it without facilitation or holding the treadmill handles. The speed of the treadmill was increased gradually and finally set at where the subject felt most comfortable and similar to his/her normal walking speed. This introduction procedure typically took about three to five minutes.

The data collection started when the subject took the formal treadmill walking test. The RW group was required to walk on the treadmill without any facilitation for one minute. And their performance was considered as the baseline measurement.

The VR group took the same one-minute walking task repeatedly with the HMD worn all the time. The first trial was considered as the initial phase of the VE exposure. Following that, five to ten more trials within fifteen minutes were conducted for them to get used to the VR walking as much as possible. Rest was allowed between trials and subjects were orally examined from time to time to make sure they didn't develop serious motion sickness. The last one-minute walking trial was measured as the habituated phase of VE exposure.

MaxLE computation

The computation of maxLE generally involves two major steps: reconstructing a state space (SS) from the original time series data to preserve information about the system dynamics as much as possible; and tracking the average divergence of the neighboring trajectories in the state space as a measurement of the system's resistance to small perturbations (Lockhart & Liu, 2008).

For the first step, most previous studies used a time delayed embedding technique to reconstruct a state space from a single-dimensional time series data (e.g. velocity in the anterior/posterior direction) (Abarbanel et al., 1993). However, since the VR walking conditions have not been thoroughly investigated and it was not clear which dimension of kinematic data contained most information about the system's dynamics, this study used a six dimensional natural state space as defined by the formula:

$$SS = [Px, Py, Pz, Vx, Vy, Vz] \quad (1)$$

where P was the marker position and V was the velocity. The raw kinematic data and the filtered data (Butterworth filter, 4^{th} order, cutoff 6Hz) were utilized to construct two state spaces (raw-SS and filter-SS) respectively.

In the second step, for each data point from a state space, its "nearest neighbor" in this state space but from different gait cycles was identified. The Euclidean distance between these two points was then tracked through time as a measurement of time-dependent divergence between two very similar initial conditions. This procedure was done for all the data points in the state space and an averaged divergence curve as a function of time ($d(t)$) was obtained. The maxLE was then computed by the following definition:

$$d(t)=d(0)e^{maxLE*t} \quad (2)$$

The maxLE quantified the exponential rate of the divergence and therefore a greater maxLE value indicated faster divergence and less stability.

Rosenstein's algorithm (Rosenstein et al., 1993) was used in the actual computation of maxLE by self-coded MATLAB programs (MATLAB R2007a, The MathWorks Inc., Natick, MA, USA).

Statistical Analysis

A mixed factor ANOVA model was used. The between-subject factor was the VE exposure (none/ initial/ habituated). The within-subject factors included the location of the marker (six locations) and the type of the state space (raw/ filter). These factors were first examined altogether using a three-way ANOVA model. After that, each of the factors was investigated separately using one-way ANOVA. A significant level of 0.05 was used throughout the statistical analysis.

Statistical analysis was performed in SAS JMP 8.0 (SAS Institute Inc., Cary, NC, USA).

RESULTS

Significant difference in maxLE was found between none, initial and habituated VE exposure ($p<0.0001$) using the three-way ANOVA analysis. Pairwise comparison further indicated that maxLE values increased (i.e. decreased stability) by the sequence of real world walking, VE habituation phase and VE initial phase.

Using raw-SS, significant difference in maxLE between walking conditions was found at RA ($p=0.0117$), LK ($p=0.0050$) and RK ($p=0.0001$); while using filter-SS, significant difference was found at RA ($p=0.0007$), LK ($p=0.0121$), RK ($p<0.0001$), LH ($p=0.0126$) and RH ($p=0.0174$). Table 2 summarized mean and standard deviation of maxLE for each VE condition, marker location and the state space used.

Table 2: Summary of maxLE values

		raw-SS		filter-SS	
LA	RW	.60±.15		.98±.21	
	VR-i	.78±.08		1.26±.12	
	VR-h	.69±.11		1.02±.23	
RA	RW	.50±.11		.85±.17	
	VR-i	.72±.14	*	1.28±.18	*
	VR-h	.62±.09		1.09±.08	
LK	RW	.49±.11		.74±.16	
	VR-i	.65±.04	*	.96±.11	*
	VR-h	.56±.05		.77±.07	
RK	RW	.41±.08		.64±.11	
	VR-i	.65±.07	*	.97±.08	*
	VR-h	.56±.07		.79±.06	
LH	RW	.35±.11		.52±.14	
	VR-i	.45±.11		.77±.14	*
	VR-h	.47±.09		.60±.08	

RH	RW	.35±.13	.49±.11	
	VR-i	.47±.11	.72±.14	*
	VR-h	.45±.06	.64±.11	

* indicates significant difference

Across all VE exposure conditions and state spaces, consistent decrease in maxLE (i.e. increase in stability) was found from ankles up to hip joints ($p<0.0001$).

Also, maxLE values computed from raw-SS were found to be significantly lower than those computed from filter-SS ($p<0.0001$). However, linear correlation between the two methods was fairly good ($r=0.8784$; Figure 2).

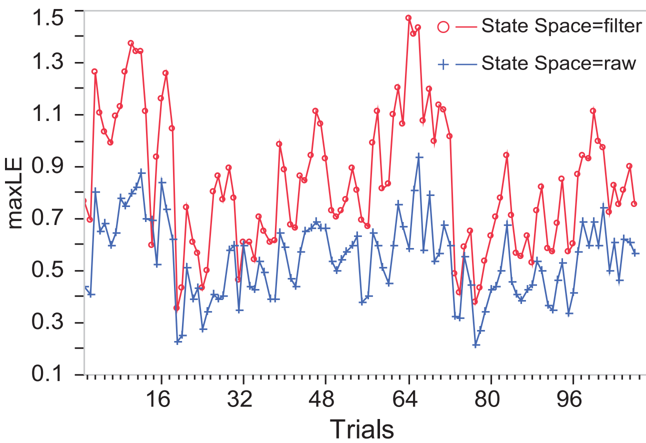

Figure 2: Comparison of maxLE values computed from raw-SS and filter-SS

DISCUSSION

Walking in the virtual environment could probably be a challenging task due to alteration of inputs to the neural-motor control system. Changes of basic balance and gait parameters caused by VE exposure were reported by different studies but a general conclusion of the VE exposure effects has not been made yet, and it was even more difficult to interpret the observed changes of parameters as positive adaptation or negative consequence. In response to that, the current study proposed a new method to evaluate VE exposure effects by using the measurement of dynamic stability. Unlike those microscopic parameters, this measurement quantifies the resistance of a dynamic system to perturbations from a macro perspective, thus could be considered as an indicator of overall system risk or task difficulty.

The significant decrease of lower extremities' dynamic stability in the elderly during VR walking compared with real world walking suggests that the involvement of VR does introduce additional perturbations that impair the regulation of gait. This finding is theoretically expectable because when walking in the real world, one receives information about his/ her segment positions from both visual system and vestibular system, while with HMD he/ she can only feel but cannot see how he/ she walks. The lost of information could cause difficulties in maintaining stability.

Fortunately, it appears that habituation in the virtual environment was quite remarkable, suggesting that even with induced perturbations, stability can recover with adjustment of gait. In other words, alterations of gait characteristics through time during VR walking could possibly represent one's effort in adapting to the virtual environment and regaining stability.

Technically, the use of multi-dimensional time series data in computing maxLE appears to be an appropriate way to preserve most information of system dynamics. Previous studies typically justified the use of single-dimensional data by the unavailability or high cost of multi-dimensional raw data (e.g. lack of 3-axis sensors). However, with the development of the sensor hardware, 3D motion capture systems and 3D inertial sensors have become common and affordable in motion study. In this situation, the full utilization of all the information collected is likely to benefit, or at least won't do harm to the assessment of system dynamics. Similar method for reconstructing state space can be found in one recent study by Kang and Dingwell (Kang & Dingwell, 2006).

Whether or not the kinematic data should be filtered is another critical issue for computing maxLE. Generally, the use of low-pass filter removes noises caused by the environment or the device but at the same time could discard useful high-frequency information that can contribute to maxLE. Although the current study found similar trend and fairly good correlation between the two methods, the selection of filter should still be made with caution and requires further investigation.

One limitation of the current study is that the effects of VE exposure we've found may be highly related to the specific HMD being tested and may not be expandable to other VR instruments. However, the preliminary results have demonstrated the possibility of gait instability in the initial phase of VE exposure and the method for assessing dynamic stability in this study can be directly adapted to evaluate other similar instruments when necessary.

Another limitation is that the current study defined the initial phase and habituated phase of VE exposure arbitrarily, while the actual time and efforts required for habituation may vary significantly in subjects. Also, the habituation process should be a progressive procedure. Correspondingly, it would be more informative if dynamic stability, instead of being two separate values for the initial and habituation phase, could be monitored continuously and expressed as a function of time.

In general, the assessment of locomotion stability during VE exposure is of great meaning to the design and evaluation of motor rehabilitation interventions for the elderly. First, it can be used to guide the task design for the VR intervention (e.g. whether or not the same walking speed in the real world and in the virtual environment indicates the same difficulty of task; how much time should be given for users to get used to the VR device). Second, it removes the confounding of instrument induced gait changes while evaluating the effects certain training programs (e.g. if the change in performance before, during and after VE exposure is only caused by the presence/absence of VE or is the real transfer or training). Finally and most importantly, results of the current study indicates the possibility of stability recovery after a certain period of VE exposure, thus supporting wider use of VR applications in motor rehabilitate for the elderly.

CONCLUSIONS

This study investigated effects of virtual environment exposure on locomotion stability in the elderly. Lower extremities' dynamic stability decreased significantly at the initial VE exposure phase. After habituation, although not fully resumed, locomotion stability was found to recover remarkably.

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