The Impact of Vibrotactile Biofeedback on the Excessive Walking Sway and the Postural Control in Elderly

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The Impact of Vibrotactile Biofeedback on the Excessive Walking Sway and the Postural Control in Elderly

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ABSTRACT
Gait and postural control are important aspects of human movement and balance. Normal movement control in human is subject to change with aging. With aging, the nervous system comprising, somatosensory, visual senses, spatial orientation senses, and neuromuscular control degrade. As a result, the body movement control such as the lateral sway while walking is affected which has been shown to be a significant cause of falling among the elderly. Biofeedback has been investigated to assist elderly improve their body movement and postural ability, by supplementing the feedback to the nervous system. In this paper, we propose a wearable low-power sensor system capable of characterizing lateral sway and gait parameters. Then, it can provide corrective feedback to reduce excessive sway in real-time via vibratory feedback modules. Real-time and low-power characteristics along with wearability of our proposed system allow long-term continuous subjects' sway monitoring while giving direct feedback to enhance walking sway and prevent falling. It can also be used in the clinics as a tool for evaluating the risks of falls, and training users to better maintain their balance. The effectiveness of the biofeedback system was evaluated on 12 older adults as they performed gait and stance tasks with and without biofeedback. Significant improvement (p-value < 0.1) in sway angle in variance of the sway angle, variance of gait phases, and in postural control while on perturbed surface was detected when the proposed Sway Error Feedback System was used.

General Terms
Measurement, Design, Experimentation, Verification.

Keywords Body movement, Postural control, Gait, Lateral sway, Sway monitoring, Biofeedback

1. INTRODUCTION
Postural control is to maintain equilibrium by correcting the center of body mass to its balanced base of support [1]. Also, lateral sway is the slight side to side postural movements made by an individual while walking in order to maintain a balanced position. Having a good postural and lateral sway control is quite important to the older individuals as it indicates a lower possibility of falling, which may bring not only health hazards but also loss of confidence, restriction of physical activities and social isolation. Therefore, the research on enhancing body sway and postural control for older adults has gained much attention from the scientific community [2, 3].

Many of the previous studies have focused on observing body movement using optical-based marker and camera equipment [4] such as, the VICON system [5] which has a high accuracy. However, they are very expensive and have major limitations considering the challenges associated with the vision and image processing. Because the position of cameras is fixed, there is limited field of view and the subjects have to move in a very limited area. Additionally, it is difficult to give direct feedback to the subjects using such systems. On the other hand, MEM-based wearable inertial sensors appear to provide an attractive solution for monitoring motor functions due to their low costs, the ability to be worn at all times, and possibility of giving real-time feedback to the subjects [6].

Lateral sway while walking, in addition to other gait parameters have been shown to be a significant cause of falling among the elderly. Therefore in this paper, we propose a wearable low-power sensor system capable of identifying sway and gait parameters and providing corrective feedback to help the subjects improve their postural control. The proposed system is capable of characterizing different parameters of sway and gait during walking. At the same time, the biofeedback system, consisting of vibratory feedback modules, provides corrective feedback to alert the individual of an excessive sway.

Our system consists of several modules including a low-power microcontroller, MEMS-based motion sensors, Bluetooth low energy (BLE) transceivers, a battery, and vibrator modules for feedback. Based on the proposed system, we designed a training protocol for subjects to wear the system to investigate its ability to improve postural control. The subjects wore the system on their chest, and the vibratory modules were attached on their upper arms. When operating, our proposed system collected walking data of subjects in real-time via the motion sensor, which includes a 3-axis accelerometer and a 3-axis gyroscope. Then, the data was fed to the micro-controller and the lateral sway angle of subject was calculated using the direct cosine matrix (DCM) based motion fusion algorithm [7]. If the sway angle exceeded an adaptively fixed threshold, which indicated that the subject was not properly controlling the sway movement, the vibratory modules were triggered to provide alerts and to train the subjects to reduce sway. The subjects also wore our designed motion sensor system on their ankles in order to record data for the gait

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phase analysis. All the motion data and the status of the vibratory modules were concurrently transmitted to the laptop via a BLE module for further analysis. Real-time and low-power characteristics along with wearability of our proposed system allow long-term continuous monitoring of the subjects walking sway while giving direct feedback to prevent falling.

The subjects were divided into an experimental group which received corrective feedback in a training phase, and a control group which received no feedback during a training phase. Each of the groups followed the same training protocol and their performance was evaluated and compared for the pre-training test, post-training test, respectively. The effectiveness of the biofeedback system was evaluated and an overall effect of reduced sway angle was investigated with and without biofeedback using statistical tests.

The rest of the paper is organized thus: In Section 2, we introduce related works and the direct cosine matrix algorithm. In Section 3, the software and hardware architecture of the proposed wearable sensor system is briefly introduced. The training protocol and the details of data collection are discussed in Section 4. In Section 5, the experimental results are reported and compared. Section 6 gives the conclusion of the study while Section 7 introduces our future work.

2. LITERATURE SURVEY

2.1 Related Works

Enhancing Postural Control has attracted much attention from the research community. One approach is via augmented biofeedback systems that supplement the natural sensory inputs, providing additional sensory information about lateral sway to the nervous system. Several studies have examined the effects of biofeedback on enhancing postural control in healthy subjects and in patients with postural deficits [8]. Also, different types of feedback such as, auditory [9], vibrotactile [10], and multi-modal feedback have been provided and their effect on postural stability in both young [11] and elderly healthy subjects [12] was successfully verified by reducing body sway. In [13], employing vibrotactile feedback to help patients with postural control deficits was investigated. In this study, the sway angle of the subjects was used to trigger the vibratory modules on the trunk if the subject leans to the sides. The focus of this work was on body tilt while standing. Their results illustrate that vibrotactile feedback based on the tilt angle can improve the balance of patients who have postural control deficits. In another study, [14] the influence of visual feedback on postural control was studied while standing. The experimental results show that if a stable marked reference was given to the subject (e.g. a laser point), the subject would have better postural control. In [9], auditory-biofeedback was employed to help the subjects improve their balance while standing. Their feedback was based on accelerometer reading on the trunk. If the subject was leaning toward one side, a stereo sound would be given to them via a headphone. In [15], the same research group moved to their research to bipedal stance [16] where they used the IMU module in the cellphone as the motion sensor and generated promising results.

As mentioned above, several effective studies on the impact of biofeedback on postural control is investigated focusing on the subject stance. However, we believe that lateral sway while walking and other gait parameters are worth more attention and investigation as it is a significant cause of falling among the elderly. Inertial sensors offer a mobile option to obtain body posture and motion for healthcare assessment and assistants as they do not require stationary installations to operate [17]. Also, inertial sensors could be noninvasively integrated in personal accessories [18]. Therefore in this paper, we propose a wearable low-power inertial sensor system capable of identifying sway and gait parameters and provide real-time corrective vibrotactile feedback.

2.2 Review of Direction Cosine Matrix Algorithm

In our system, we employed the direction cosine matrix algorithm (DCM). While being an effective algorithm to calculate the orientation of a rigid body [7], the calculations in DCM algorithm are made in real-time which make it a suitable choice for our real-time corrective feedback system.

In DCM algorithm, certain types of moving information such as, directions, velocities, and accelerations can be transformed between rotated references with a 3 × 3 matrix. Moving information vectors can be rotated by multiplying to a DCM.

$$R(\theta)=\begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \quad (1)$$

DCM should be orthogonal by definition. Therefore, even though it has 9 elements, only 3 of them are independent. For coordinate transforms, $R(\theta)$= A, the appropriate direction cosines a_{ij} are defined as follows (the left index indicates the new axis and the right index indicates the old axis):

(2)

		Old axes x	y	z
	x`	a_{11}	a_{12}	a_{13}
New axes	y`	a_{21}	a_{22}	a_{23}
	z`	a_{31}	a_{32}	a_{33}

where

$$\begin{aligned} a_{12} &= a_{x`y} = \cos\theta_{x`y}, \\ a_{13} &= a_{x`z} = \cos\theta_{x`z}, \\ a_{23} &= a_{y`z} = \cos\theta_{y`z} \end{aligned} \quad (3)$$

The rest of the components in the DCM can be obtained based on the above three components. The relationship between the DCM and Euler angles is given by:

$$R = \begin{pmatrix} \cos\theta\cos\omega & \sin\phi\sin\theta\cos\omega - \cos\theta\sin\omega & \cos\phi\sin\theta\cos\omega - \sin\phi\sin\omega \\ \cos\theta\sin\omega & \sin\phi\sin\theta\sin\omega - \cos\theta\cos\omega & \cos\phi\sin\theta\sin\omega - \sin\phi\cos\omega \\ -\sin\theta & \sin\phi\cos\theta & \cos\phi\cos\theta \end{pmatrix} \quad (4)$$

where θ stands for the roll axis rotation angle, ϕ stands for the pitch rotation angle, and ω stands for the yaw rotation angle, respectively.

3. SYSTEM ARCHITECTURE

3.1 Hardware Architecture

Our lab-made wearable motion sensor board consists of 5 parts: the micro-processor, motion sensor chip, Bluetooth low energy

(BLE) transceiver, vibratory module and battery as shown in Figure 1.

The TI MSP430F5528 micro-controller is used as the processor, managing all the data processing, communication and feedback. The MEMS based motion sensor Invensense MPU9150 provides a 3-axis accelerometer (±2g), a 3-axis gyroscope (±2000°/s) and a 3-axis magnetometer. We only use the data from the accelerometer and gyroscope to calculate the sway angle. To stream the data out to the laptop, the Blueradio BLE transceiver CC2541 is used. The microprocessor receives the data from the motion sensor via an I^2C interface, and the sway angle readings are sent to the BLE module using URAT. The device is attached on the chest and the ankle of the subjects and monitors sway in the roll axis. The sampling rate is 40Hz. The data is transferred to a laptop in real time via the BLE transceiver. Moreover, power management circuits and an essential protection circuit are also implemented. For vibrotactile feedback, two Precision Microdrives 310-101 vibrators are used. The vibration intensity is set as default: the frequency of inner motor is 200Hz and the vibration amplitude is 0.8G.

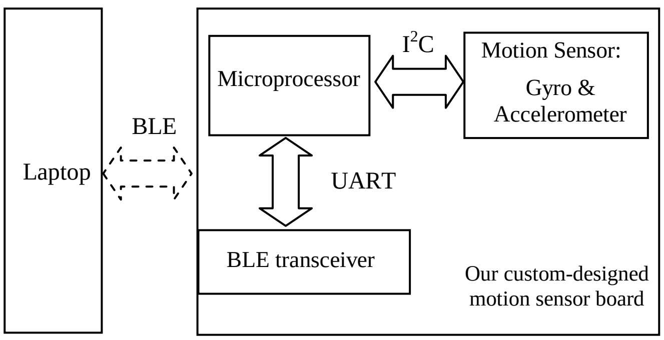


Figure 1. Hardware architecture of the proposed system.

3.2 Software Architecture

Angle estimation with IMU has been well-explored [17]. In our proposed system as shown in Figure 2, the DCM algorithm, introduced in Section 2.2, calculates the orientation of a rigid body in respect to the rotation of the earth using the rotation matrix, using the Euler angles. The sensors used in our system are used as follows:

- A gyroscope measures the angular velocity while the subject is moving.
- An accelerometer measures gravity and provides the orientation. In addition, it corrects the drift brought by the gyroscope reading.

After placing the motion sensor board on the subjects, a 5 second calibrated phase is conducted in order to reset the reference vectors. After the calibration phase, the readings from the accelerometer and gyroscope are used to update the Rotation Matrix. To get the sway angle, we set an orientation reference to the ground first and compared the present DCM to it. A PI Controller is used to correct the drift caused by the gyroscope. After the Rotation Matrix is updated, ruler angle is calculated using the DCM algorithm. The block diagram of the system software is shown below.

Also, different people have different gait parameters and the sway angle varies among the subjects accordingly. Therefore, a unified threshold to trigger the feedback would not be an accurate and effective solution. In this paper, instead of giving a unified threshold, we calculated a subject specific threshold in a self-adaptive manner. The system monitors the range sway of each subject for the first 30 seconds, and then calculates the average of sway range. The final threshold to trigger the vibrotactile feedback is set to be 80% of the calculated sway range. In this way, the threshold adapted to different walking patterns by different subjects.

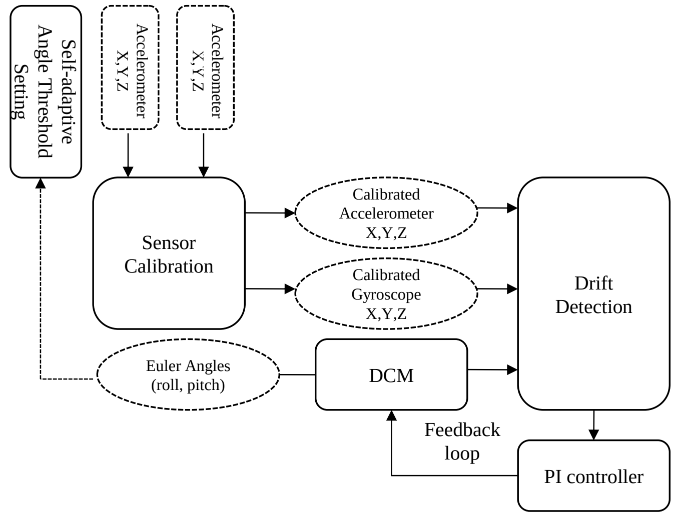


Figure 2. Software architecture of the proposed system.

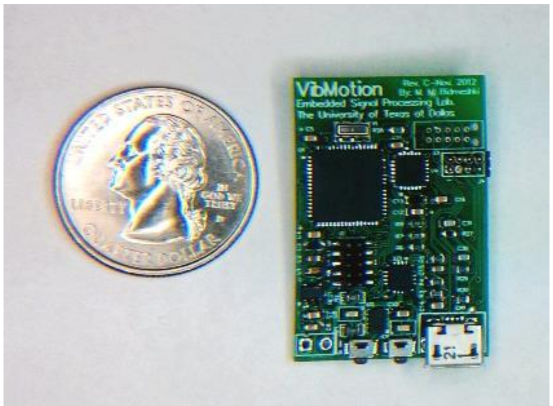
4. DATA COLLECTION AND EXPERIMENT SETUP

4.1 Subjects

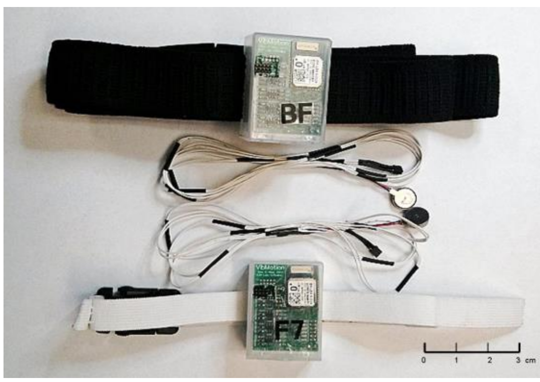
12 older adults (age: M = 75.5, SD = 4.32 years; 10 females) participated in our study. Balance and gait were evaluated using the sensory organization test (SOT) of the NeuroCom® Equitest [18] and the GAITRite Electronic Walkway. Half of the subjects were in the experimental group (n = 6) who received the corrective feedback while the other half of the subjects were in the control group who wore the equipment for the purpose of recording their sway data but did not receive any feedback. The two groups were age matched and there was one male participant in each group. All participants provided informed consent, approved by the University of Texas at Arlington Institutional Review Board.

4.2 Experimental Procedure

The experiments consisted of 3 phases: the pre-training test phase, the training phase, and the post-training test phase. All subjects started with an initial postural control assessment to obtain a baseline to compare with. Specifically, they were asked to perform the SOT and gait tasks. The SOT uses a force plate and sway referencing of the support (floor) and visual surround (wall) to challenge an individual's sensory systems in order to measure their postural control under a variety of conditions. The gait task included three rounds of normal walking for 10 meters at a preferred speed. Figure 3 shows our designed wearable low-power motion sensor board, and our biofeedback system, consisting of two motion sensor boards along with the vibratory feedback modules. When performing the gait task, the subjects wore the motion sensor board on their chest and the biofeedback system on their arms, consisting of vibratory feedback modules which provide corrective feedback to alert the individual to excessive sway as shown in Figure 4. The gait information is collected both by our motion sensor board and the GAITRite Electronic Walkway. The subjects rested for 2 minutes after this pre-training test. Also to record data from the lower limbs for the gait phase analysis, the subjects wore our designed motion sensor board on their ankles as shown in Figure 4.



(a)



(b)

Figure 3. (a) Our designed wearable low-power motion sensor board, and (b) Our biofeedback system, consisting of two motion sensor boards for the chest and the ankle along with the vibratory feedback modules.

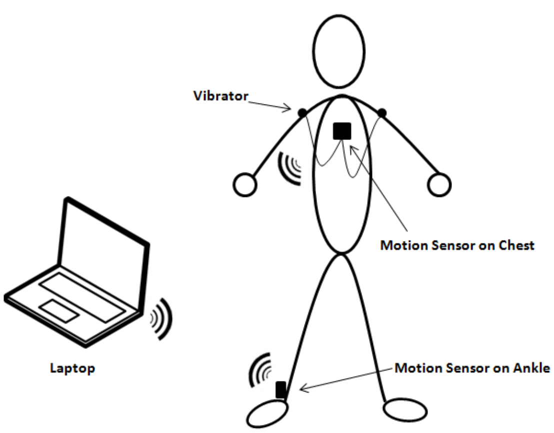


Figure 4. Schematic of our proposed biofeedback system.

After the pre-training test, all the participants received the training phase. The training phase was composed of 20-minute walk along a walking track at a gym. The 20-minute walk was divided into 4 sections considering the health condition of the subjects. Subjects were given 2 minutes of rest between each section. All of the subjects wore the motion sensor board; however, vibratory feedback modules were only attached on the arms of the subjects from experimental group so that they received feedback while training. After the training phase, subjects rested for 2 minutes and moved to the post-training test phase. Walking sway data was collected both using our designed motion sensor board and the GAITRite Electronic Walkway.

In the post-training phase, subjects from both the experimental group and the control group are asked to follow the exact protocol as in the pre-training phase in order to measure possible changes caused by the training phase. Finally, the results of the two phases were evaluated and compared.

5. RESULTS AND ANALYSIS

In this section, the results are presented and analyzed. The evaluation measures include the variances in the range of the lateral sway, the variances in different gait phases, gait changes, and changes to the Center of Gravity (COG) alignment.

5.1 Lateral sway analysis

To study the variance in the sway range, we averaged the outcome of all the three rounds of pre- and post-training tests for each of the subjects. We calculated the difference between pre-training and post-training results. The difference was calculated by subtracting the variances in the pre-training from the post-training. A negative difference indicates lower variance in lateral sway.

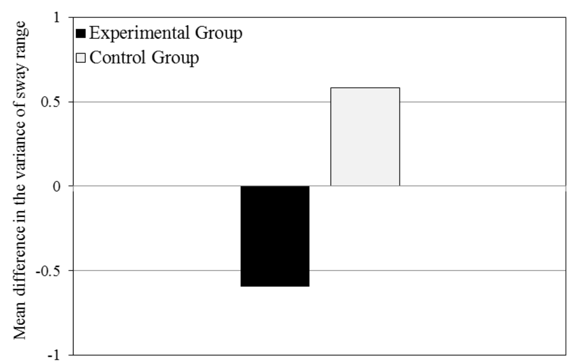


Figure 5. Mean difference in the variance of sway range.

Table 1. The results of the Chi-square test on the sway range

The test	Control	Experimental	P-value
Difference in the Variance of Sway Range	0.59±1.77	-0.60±0.63	0.04

Figure 5 illustrates the calculated differences in the variances between pre- and post-training tasks for the experimental and the control groups. As shown in Figure 5, the mean difference is positive for the control group which shows that an excessive variance is introduced to the lateral sway from the pre- to post training session. On the other hand, the mean difference is negative for the experimental group which shows lower variance in the lateral sway and better control with their walking pattern after the feedback training phase. We also conducted a Chi-square variance test to compare the variances in the sway range for the experimental and the control groups. The result of the Chi-square variance test in Table 1 shows that the variance in the sway range become significantly lower for the experimental group after the proposed feedback training (p-value = 0.04).

5.2 Gait phase analysis

In gait analysis, the lower limbs provide stability rather than range of motion and that stability is achieved at most of the major joints of the lower limb. Gait cycle is a series of rhythmic movements of the lower limbs, upper limbs with the trunk leading to forward progression of the center of gravity [19]. Figure 5 shows an example of a walking cycle starting from the time the big toe of one foot leaves the ground to the time the same foot completely touches the ground.

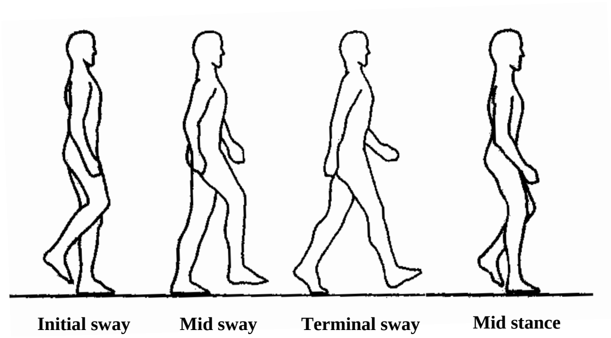


Figure 6. An example of the phases of a gait cycle.

To evaluate the gait phases shown in Figure 6, the subjects wore our designed motion sensor board as illustrated in Figure 3(a) on their ankles. We recorded the data from the board during the pre- and post-training sessions. Then, using the BSN visual software tool developed by our lab, we aligned the readings from the gyroscope and the accelerometer with simultaneous video recording as the ground truth. Then, we extracted the phases of a gait cycle shown in Figure 6 based on their associated video (Std. < ±100ms) from the accelerometer recording in the yaw axis as it led to the most robust pattern for the gait cycle shown in Figure 7.

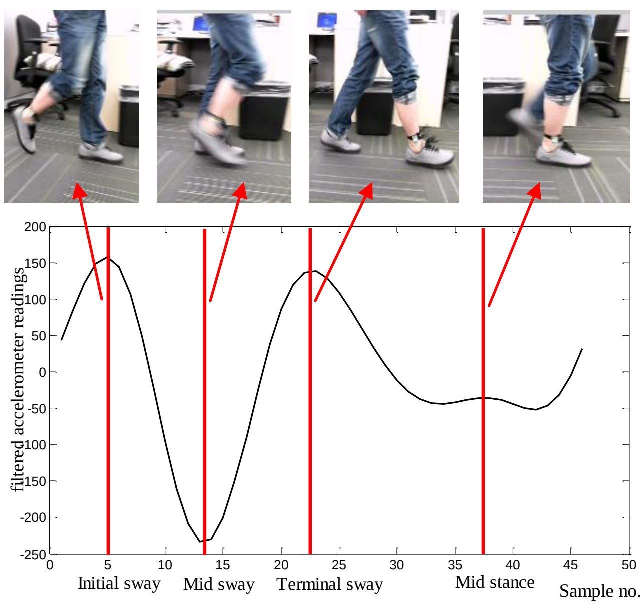


Figure 7. Identification of the gait phases on the accelerometer readings (on the y axis, 256 and -256 stand for 1g and -1g Acceleration, respectively).

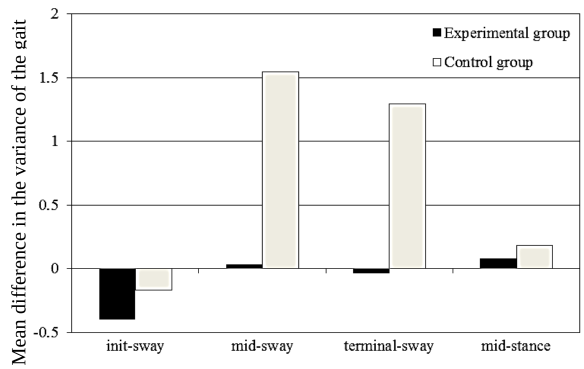


Figure 8. Mean difference in the variance of the gait phases between pre- and post- training sessions.

We used the template shown in Figure 7 as the template, and employed Dynamic Tim Warping (DTW) to extract the gait cycles and phases for different subjects. We investigated the variances in different gait phases by averaging the outcome of all the three rounds of pre- and post-training tests for each of the subjects. We calculated the difference between pre-training and post-training results similar to the Section 5.1. The difference was calculated by subtracting the variances in the pre-training from the post-training. A negative difference indicates lower variance in lateral sway.

Figure 8 shows the calculated differences in the variances of the gait phases between pre- and post-training tasks for the experimental and the control groups. As shown in Figure 8, the mean difference of the experimental group is lower than that of the control group in all the gait phases which shows lower variance in the lateral sway. Therefore, this observation verifies that the proposed corrective feedback system is effective toward more stable gait, and better balance control. We also conducted a Chi-square variance test to compare the difference in the variance of the gait phases for the experimental and the control groups. The result is reported in Table 2.

Table 2. The results of the Chi-square test on the gait phases

The gait phases	Control	Experimental	P-value
Initial sway	0.17±0.62	0.40±0.15	0.19
Mid sway	-1.54±1.72	-0.03±0.48	0.08
Terminal sway	-1.29±1.04	0.038±1.01	0.05
Mid stance	-0.18±0.89	-0.07±1.14	0.27

Table 2 illustrate that the variance in the mid sway and the terminal sway become significantly lower for the experimental group after the proposed feedback training compared to the control group (p-values of 0.08 and 0.05, respectively). However, the differences are not significant for the initial sway and mid stance phases (p-values of 0.19 and 0.27, respectively). The reason for the significant impact of the feedback system on the mid sway and the terminal sway may be that the corrective vibration to alert the individual of an excessive sway takes effect right before the occurrences of these two gait phases.

5.3 Gait Changes

Measures of gait changes related to fall risk, specifically those collected by the GAITRite, were analyzed to determine if any pre-post differences were present. Significant interactions of time (pre vs. post) and condition (experimental vs. control) were present for Velocity, Cadence, and the Coefficient of Variation (CV) for Stride Length (p-values of .09, .09, and .08, respectively). All other gait comparisons were not significant. For these three variables, the results indicate that control participants' performance declined following the intervention, while experimental participants' performance was maintained.

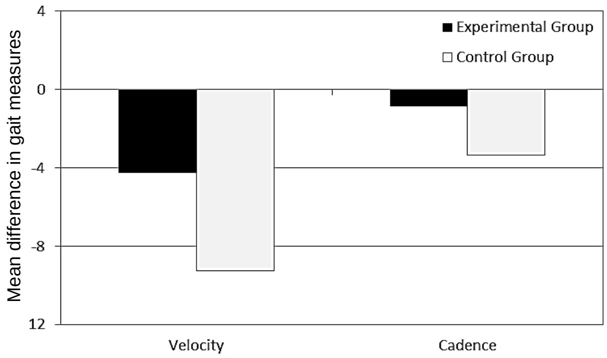


Figure 9. Mean difference in gait measures related to falls between pre- and post- training sessions.

Figure 9 illustrates the calculated differences in Velocity and Cadence between pre- and post-training tasks for the experimental and the control groups. Figure 9 shows that while the both groups' Velocity declined, the experimental group showed less of a decline. Additionally, the experimental group maintained a similar Cadence (steps/min) from pre- to post-test while the control group's Cadence slowed.

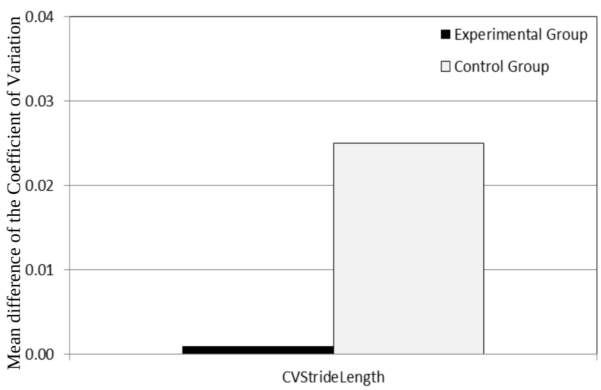


Figure 10. Mean difference of the Coefficient of Variation (CV) for Stride Length pre- and post- training sessions.

Figure 10 illustrates the calculated difference in the Coefficient of Variation for Stride Length between pre- and post-training tasks for the experimental and the control groups. Although the experimental group shows no significant change in stride length variability, the control group became more variable after the intervention than they were prior to the intervention. Taken together with the Velocity and Cadence data, these indicate that the control group was walking more slowly, taking steps less often, and was less consistent (i.e. more variable) in the steps they were taking following the intervention. Conversely, the experimental group was better at maintaining their pre-test scores.

5.4 Center of Gravity (COG) Changes

As this experiment focused on providing feedback about lateral sway, it was hypothesized that this feedback may also affect center of gravity (COG) alignment during standing. This was measure during the sensory organization test (SOT). Analyses revealed a significant interaction of time (pre vs post) and condition (experimental vs. control) for the lateral (x) axis (p-value of .07). However, there was no significant interaction for the anterior-posterior (y) axis (p-value of .23).

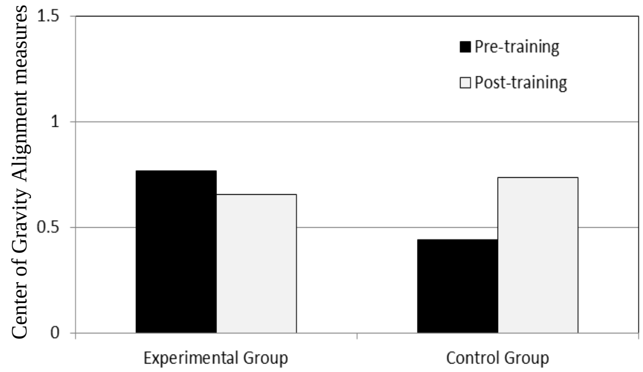


Figure 11. Center of Gravity Alignment measures on the x-axis for pre- and post- training sessions.

Figure 11 illustrates Center of Gravity Alignment measures on the x-axis for each group at both pre- and post-training sessions. Participants in the experimental group maintained their alignment while participants in the control group became more lateralized.

6. CONCLUSION AND FUTURE WORK

In this paper, we proposed a wearable low-power sensor system capable of characterizing lateral sway and gait parameters. Our designed system provides corrective feedback in order to reduce excessive sway in real-time via vibrotactile feedback modules. We investigated the short-term effect of lateral sway monitoring and correction for older adults while walking. The effectiveness of the biofeedback system was evaluated on 12 elderly subjects as they performed gait and stance tasks. The subjects were divided into the experimental group which receives corrective feedback in the training phase, and the control group which receives no feedback. Comparing the performance of the two groups in the pre- and post-training test, we found that vibrotactile biofeedback training improves lateral sway and posture control, and the effect was evident in the post-training test. Real-time and low-power characteristics along with wearability of our proposed system allow long-term continuous monitoring of subjects' walking sway while giving direct feedback to prevent falling. Therefore, our future direction is toward the long-term impact of our designed vibrotactile feedback system. In this way, we intend to investigate the effect of 5-week excessive sway feedback training in older adults.

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