7-17-2020

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Gait & Posture 81 (2020) 126–130

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

A head-worn display ("smart glasses") has adverse impacts on the dynamics of lateral position control during gait

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ARTICLE INFO

Keywords:
Gait variability
Stability
Goal equivalent manifold
Maximum lyapunov exponent
Head-worn displays

ABSTRACT

Background: Head-worn displays (e.g., "smart glasses") are an emerging technology to provide information, and in many situations they might be used while walking. However, little evidence exists regarding the effects of head-worn displays on walking performance. We found earlier that "smart glasses" had smaller adverse effects on measures of gait variability in the anterior-posterior direction vs. other types of information displays. Participants, however, complained about motion sickness and perceived instability while using smart glasses.
Research question: Were the participants' complaints a result of adverse effects of the smart glasses on the dynamics of lateral stepping and gait stability?
Methods: Twenty individuals walked on a treadmill in four different conditions; single-task walking, and three dual-task walking conditions, the latter using smart glasses, smartphone, and a paper-based system to provide secondary cognitive tasks. We assessed the dynamics of lateral stepping and gait stability using the goal equivalent manifold and maximum Lyapunov exponent, respectively.
Results: The dynamics of the lateral stepping were more adversely affected using smart glasses compared to the other types of information displays. However, stability measures revealed that the participants were more unstable when they used the smartphone and paper-based system.
Significance: Promising results in terms of stability and adaptability suggest that head-worn display technology is a potentially useful alternative to smartphones and other types of information displays for reducing the risk of a fall. Results regarding perceptions of instability and a loss of control over lateral stepping, however, imply that this technology requires further development prior to real-work implementations.

1. Introduction

So-called "smart glasses" are a type of head-worn display technology that functions as a computer and enables individuals to view information within their visual field of view in real time. This new technology allows individuals to both maintain a head-up posture and to use both hands freely while performing diverse tasks (e.g., reading text messages). Particularly in the occupational domains, smart glasses may enhance worker performance [1,2]. Given these opportunities, smart glasses are considered by some (e.g., tech companies) as an alternative for smartphones, and several industries are considering the near-future adoption of this technology in their workplace [3]. This wearable technology, however, is relatively new to both individuals and industries, and there is the potential for adverse safety impacts [3], especially walking performance. Falls, in particular, are one of the top causes of injuries and injury-related deaths [4], and dual-task walking increases the risk of these events [5]. As such, there is a need to better understand the risk of falls while using smart glasses.

Fall risk can be evaluated by measuring variations in gait parameters and quantifying walking stability [6]. Since the human body has a large number of muscles and joints, the central nervous system (CNS) can use different muscle activity patterns and joint configurations to perform a given task [7]. The existence of multiple motor solutions for achieving the same task is called equifinality [8], and leads to the presence of variations in repetitive tasks (e.g., walking) [9]. In a simple walking task, the CNS has access to sufficient cognitive resources to perform the task. During dual-task walking (with a secondary task such as reading), cognitive resources are allocated to both walking and the secondary task. When the cognitive demand of performing both tasks exceeds limited cognitive recourses, the capabilities of the CNS to utilize multiple walking solutions (source of variability) and overcome external perturbations declines (stability) [5]. Consequently, both

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https://doi.org/10.1016/j.gaitpost.2020.07.014
Received 9 October 2019; Received in revised form 11 July 2020; Accepted 15 July 2020
0966-6362/

measures of walking stability [10] and gait variability [10,11] will be affected, suggesting a higher risk of falls. As such, the risk of falls while using smart glasses can be evaluated by quantifying the effects of their use on gait stability and variability.

In an earlier study [12], we began to address such safety concerns by comparing the effects of smart glasses and two traditional handheld devices (i.e., paper based system and smartphone) on gait variability. Our results suggested that the handheld devices had adverse impacts on gait variability, but not the smart glasses [12]. However, the responses of the participants to usability questionnaires were contradictory to the results regarding gait variability. Specifically, participants noted instability while using smart glasses. In this earlier study, however, we only assessed kinematic variability in anterior-posterior (AP) direction. Previous work, though, indicates that the CNS uses different walking goals in the AP and medio-lateral (ML) directions to maintain balance on a treadmill [13]. The results of this study suggest that the properties of variability are independent in the AP and ML directions. Earlier studies also showed that humans are more unstable in the ML direction during walking [14,15]. As such, we suggest that the noted perceptions of instability might have stemmed from negative effects of smart glasses on lateral stepping dynamics. Furthermore, variability is not equal to stability [16]; thus, a direct measure of stability, such as the local divergence exponent [17], could help reveal the reasons behind perceptions of instability.

To understand how different information displays affect lateral stepping dynamics, we need a framework that can explain how humans regulate their steps. Recently, the goal equivalent manifold (GEM) offers such a framework, to address how humans regulate their movement based on the equifinality concept [18]. Previous studies have used this framework successfully to study motor control strategies utilized by the central nervous system for different tasks [19–21]. Dingwell and Cusumano [13] extended this framework to the mediolateral (ML) direction, which can be used to understand how humans change their lateral stepping strategy to adapt to a new walking condition (e.g., dual-task walking).

Thus, the first aim of our study was to examine the effects of information displays on lateral stepping dynamics using the GEM framework. We hypothesized that only smart glasses will have an adverse impact on gait variability in the ML direction. The second aim was to quantify the effects of information displays on the local divergence exponent, as a direct measure of stability. Similar to variability, we hypothesized that stability outcomes will only be adversely affected by the smart glasses.

2. Method

2.1. Participants and procedures

We completed a secondary analysis of data from a previous study [12], in which 20 healthy young adults walked on a treadmill at their preferred walking speed in four 5-minute walking trials. The participants included 10 females (age = 22.3 (2.5) years; weight = 66.2 (13.5) kg; height = 164.5 (7.6) cm) and 10 males (age = 23.9 (3.2) years; weight = 74.8 (13.0), height = 176.5 (12.6). These experimental trials involved one single-task walking (ST) and three dual-task conditions using different information displays (walking while using a paper-based system, smartphone, and smart glasses). During the dual-task walking conditions, participants needed to perform several attention-demanding cognitive tasks, including the Stroop test, categorizing, and arithmetic, which were each presented by the information displays (Fig. 1). Participants adopted a “head-up” posture for the ST and dual-task smart glasses (DT-glass) conditions, while they used a “head-down” posture for the dual-task paper based system (DT-paper) and smartphone (DT-phone) conditions. To minimize confounding effects related to trial order, we counterbalanced the order of conditions. Reflective markers were placed on the participants’ trunk and lower body to capture 3D segmental kinematics during the walking trials, which tracked by a 7-camera system (Vicon Motion System, CA, USA) at 100 Hz. After completing the walking conditions, the participants provided a list of advantages and disadvantages of each of the displays. (For more details about experimental procedures and participants, please refer to [12].)

2.2. Data analysis

Dingwell and Cusumano [13] recently examined the regulation of lateral stepping movements across consequent steps, by extending their GEM-based computational model to the ML direction. They tested several potential walking goals that humans might adopt to maintain lateral balance. These walking goals included maintenance of lateral position (z_B), heading (Δz_B), step width (Fig. 2), and different paired combinations of these. An important finding in their work was that a model that simultaneously controlled z_B & w, and that prioritized control of step width over lateral position, could replicate experimental data [13]. These results suggest that humans maintain multiple goals in the ML direction to regulate their steps laterally, specifically keeping step width and lateral position consistent. Based on the GEM framework, variations in z_B & w are equivalent to variability in the GEM direction, and quantifying the size and structure of variability of these two gait parameters could provide new information related to falls risk related to ML control.

To quantify the variability of z_B & w, we first identified heel strike events by implementing a common algorithm [22]. Based on this algorithm, a heel strike event is identified when the AP distance between the hip and heel markers is at a maximum. Thereafter, left and right foot placements (z_L and z_R; Fig. 2) were defined as locations of the heel markers in the ML direction at each step [13]. From the unfiltered lateral foot placement time series (z_L and z_R), we calculated the time series of lateral position ($z_B = \frac{z_L + z_R}{2}$) and step width ($w = z_R - z_L$) [13]. We then computed the standard deviations (SD) of z_B and w to quantify the magnitude of variability in these two variables. We also used de-trended fluctuation analysis (DFA; see Peng et al. [23]) of these time series (i.e., z_B and w) to measure the temporal structure of variability. DFA provides a scaling exponent (α) for gait-relevant variables (here, z_B and w) and shows how rapidly these gait variables are corrected with subsequent steps [18]. A lower value of α (closer to 0.5) for a time series indicates that the time series is corrected more “tightly” and vice versa [13,21,24]. We computed SD and DFA values for 482 steps (the shortest number of steps across all participants and conditions) in each walking trial.

We also quantified local gait stability by obtaining the maximum Lyapunov Exponent (LyE). This nonlinear measure estimates local stability by calculating the mean divergence rate of kinematic differences between two consecutive strides [17]. Similar to an earlier study [25], we calculated the maximum LyE by implementing Rosenstein’s algorithm [26] on the incremental time series of a trunk marker (i.e., C7) for each of three movement directions (ML, AP and vertical: VT). Note that we used increments of the original data (i.e., $\Delta x(i) = x(i+1) - x(i)$) to have more stationary time series [25]. Consistent with the gait variability measure, we included 241 consecutive strides (or 482 steps) in each trial.

To calculate the maximum LyE, we first time-normalized the incremental time series of the C7 marker, such that each time series would have 101 samples per stride. Subsequently, we determined the time-delay (τ) and embedding dimension (d_E) of the time series based on the autocorrelation [26] and false nearest neighbors (FNN) algorithms [27], respectively. Time delays in the ML, AP, and VT directions were 17, 11, and 8 samples, respectively. Based on the FNN results, and consistent with earlier studies [17,25], we set $d_E = 5$. Thereafter, we used the Tisean package (version 3.0.0) to obtain the mean logarithmic divergence curve based on Rosenstein’s algorithm. Finally, the short-term LyE (λ_s) and the long-term LyE (λ_L) were measured by calculating

Fig. 1. Illustration of the smartphone (left), smart glasses (middle), and paper-based system (right).

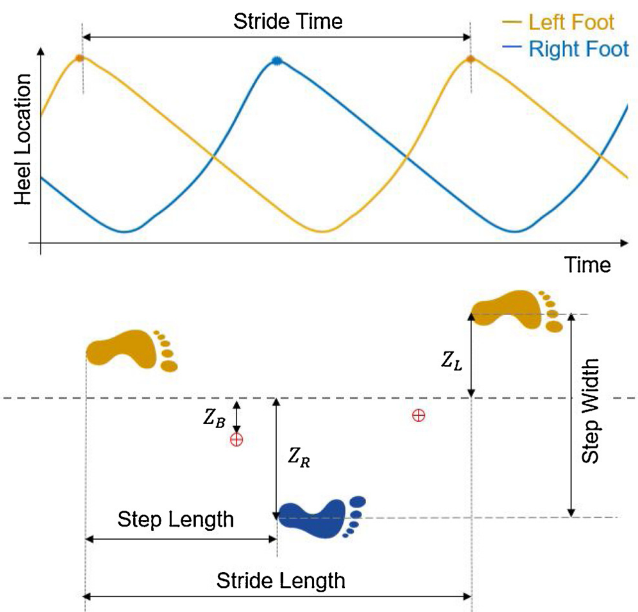

Fig. 2. Basic gait parameters for quantifying gait variability.

the slopes of the linear least-squares fits to the average logarithmic divergence curve, respectively between the 0th and 1st stride and between the 4th and 10th stride. Higher values of LyE indicate lower stability and vice versa.

2.3. Statistical analyses

The effects of different display conditions (DC: none, phone, paper, and glass) and gender (G) on the GEM and LyE outcomes were investigated by using separate mixed-factor analyses of variance (ANOVAs). Note that we included G as an independent variable in our statistical model because previous studies have found gender differences in movement variability and stability (reviewed in [28]). We tested parametric model assumptions, and used log transformations for models with non-normally distributed residuals (i.e., $SD(Z_B)$, $SD(w)$, $\alpha(w)$, λ_{L-ML}, and λ_{L-VT}). We considered p-values < 0.05 as statistically significant. Post-hoc paired comparisons were done using the Tukey HSD method, and summary results are presented as least-square means (with 95 % confidence intervals) in the original units. Effect sizes are reported using partial eta-squared (η_p^2).

3. Results

3.1. Variability in the ML direction

Main effects of DC were significant on all variability outcomes except SD of step width (Table 1). In all three dual-task conditions, participants exhibited significantly higher variations in lateral position (z_B) compared with the single-task (Fig. 3, top left). The DT-glass had higher impacts on SD of lateral position (z_B) compared to DT-phone (Fig. 3, top left). Outcomes from DFA analysis indicated that participants corrected their step width more frequently compared to lateral position (Fig. 3, bottom). In addition, the DT-glass was the only condition that disturbed the regulation of lateral position (Fig. 3, bottom left). Regarding step width, participants appeared to regulate this gait parameter more frequently during the DT-paper ($p = 0.002$) compared with the single task. We observed a similar difference for regulation of step width in the DT-phone condition compared with the single-task, though it only approached significance ($p = 0.098$).

Table 1
Summary of ANOVA results related to the effects of display conditions (DC) and gender (G) on *variability* outcomes in the ML direction. *P*-values (p), with effect sizes (η_p^2) in parenthesis, are provided for each effect, and bold font highlights significant effects.

Outcome	DC	G	DC × G
SD (z_B)	**< 0.001 (0.518)**	0.301 (0.021)	0.811 (0.017)
SD (W)	0.269 (0.070)	0.244 (0.026)	0.132 (0.010)
α (z_B)	**< 0.001 (0.381)**	0.801 (0.001)	0.755 (0.022)
α (w)	**0.004 (0.216)**	0.865 (< 0.001)	0.311 (0.063)

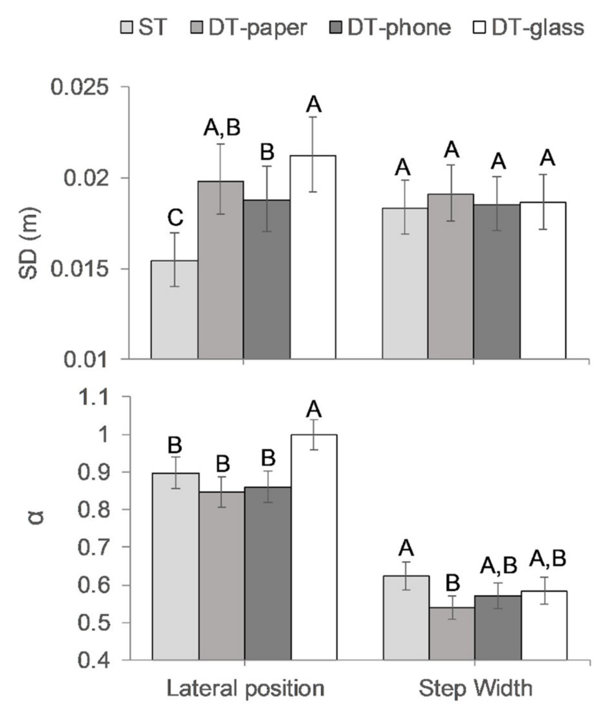

Fig. 3. Variability of lateral position (z_B) and step width (w) in the ML direction. Mean values are presented using the standard deviation (SD, top) and α obtained detrended fluctuation analysis (DFA, bottom), and are given separately for the different experimental conditions: single-task walking (ST), and for dual-task walking while using the paper-based system (DT-paper), the smartphone (DT-phone), and the smart glasses (DT-glass). Error bars indicate 95 % confidence intervals. Results from paired comparisons among the four experimental conditions are shown using capital letters; values with different capital letters are significantly different.

Table 2
Summary of ANOVA results related to the effects of display conditions (DC) and gender (G) on *stability* outcomes. *P*-values (*p*), with effect sizes (η_p^2) in parenthesis, are provided for each effect, and bold font highlights significant effects.

Outcome	DC	G	DC × G
λ_{s-AP}	< **0.001 (0.515)**	0.267 (0.024)	0.572 (0.036)
λ_{s-ML}	< **0.001 (0.512)**	0.977 (< 0.001)	0.752 (0.022)
λ_{s-VT}	< **0.001 (0.343)**	0.743 (0.002)	0.541 (0.039)
λ_{L-AP}	0.279 (0.068)	0.247 (0.026)	0.695 (0.026)
λ_{L-ML}	0.117 (0.102)	0.449 (0.011)	0.888 (0.012)
λ_{L-VT}	0.433 (0.049)	0.970 (< 0.001)	0.645 (0.030)

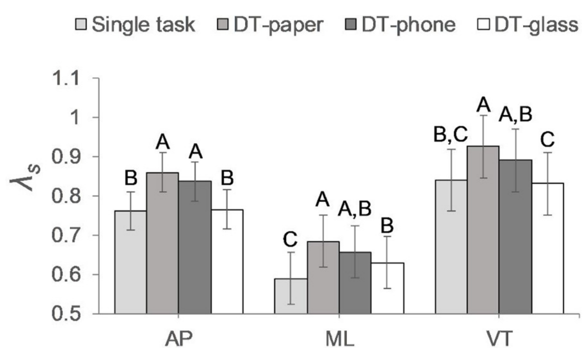

Fig. 4. Stability outcomes in the anterior-posterior (AP), medio-lateral (ML), and vertical (VT) directions. Mean values of short-term finite-time Lyapunov exponents (λ_s) are presented for the four experimental conditions: single-task walking (ST), and dual-task walking while using the paper-based system (DT-paper), the smartphone (DT-phone), and the smart glasses (DT-glass). Error bars indicate 95 % confidence intervals. Results from paired comparisons among the four experimental conditions are shown using capital letters; values with different capital letters are significantly different.

3.2. Stability outcomes

There were significant effects of DC on λ_s in all directions, but not on λ_L (Table 2). In the AP and VT directions, λ_s in the DT-paper and DT-phone condition were significantly higher than in the single-task and DT-glass conditions (Fig. 4), except for the DT-phone condition in the VT direction, in which the difference only approached significance ($p =$ 0.080). In the ML direction, short-term local stability significantly decreased with the dual-task conditions and these decreases were more pronounced for the DT-paper and DT-phone (Fig. 4, middle).

4. Discussion

Despite the potential benefits of smart glasses [1,2], this new technology may increase the risk of falls. In a prior study [12], we found that gait variability outcomes in the AP direction were less affected by the smart glasses compared with the smartphone and paper-based information displays. These earlier results suggested that the risk of falls while using smart glasses might be lower than when using smartphone or paper-based systems. Our participants, however, raised several concerns related to the use of smart glasses, and complained about motion sickness and instability. Since smart glasses affected perceptions of stability, but not gait variability outcomes in the AP direction, we speculated that smart glasses might have adverse effects on the dynamics of lateral stepping and/or local stability.

The use of a new computational algorithm, based on the GEM framework [13], showed that a possible strategy to control lateral balance in healthy young adults is to control step width (w) and lateral position (z_B) simultaneously. As such, we first hypothesized that using smart glasses disturbed regulation of these two parameters. Our results supported this hypothesis for regulation of lateral position, but not step width. The size of variations in lateral position (i.e., SD (z_B)) increased during the dual-task conditions, and this increase was more substantial for the DT-glass (Fig. 3, Top left). More importantly, DFA analysis showed that α (z_B) for the DT-glass was higher than in all other conditions (Fig. 3, Bottom left). Consistent with earlier interpretations [13,21,24], a higher α value for z_B in the DT-glass condition suggests that participants corrected variations in this variable less frequently and with lower control. These results, together with our prior findings [12], imply that participants' perceptions of instability and dizziness were likely due to loss of control over lateral position. Our results also support the predictions of Dingwell and Cusumano's computational model [13], which suggested that control of lateral position plays a key role in maintaining lateral balance. Similar to findings of an earlier study [13], values of α (w) in all the current walking conditions were lower than α (z_B), indicating that participants' control of step width was much tighter than lateral position. While participants weakly controlled lateral position (i.e., z_B), losing control of z_B may have caused undesired feelings (e.g., motion sickness) and may increase the risk of a fall.

We also hypothesized that using smart glasses during walking would have more adverse effects on gait stability than the paper-based system or smartphone. The stability outcomes did not support this hypothesis. Higher values of the short-term LyE in the AP and VT directions found in the DT-paper and DT-phone condition compared with ST and DT-glass (Fig. 4) suggest lower stability for the former conditions [25,29]. Consistent with our finding based on gait variability measures in the AP direction [12], these results imply that risk of fall might be lower in the DT-glass condition. In the ML direction, however, local stability (i.e., the capability of the CNS to overcome external perturbations) decreased in all of the DT conditions. One possible reason that stability was affected by the smart glasses only in the ML direction, but not in the other directions, is that human walking is more unstable in the lateral direction [30]. Consequently, external perturbations due to dual-task activities during gait may have more pronounced effects on stability in the ML direction. Since the participants here did not have any prior experience in using the smart glasses, they may have needed to explore more motor solutions in the ML direction to overcome external perturbations in this walking condition. As we discussed earlier, the participants appeared to implement looser control over lateral position (z_B) in the DT-glass condition. Together, these results imply that the participants explored more motor solutions by reducing control over the lateral position. Although the short-term LyE increased in the ML direction in all three of the DT conditions, participants were more stable during the DT-glass condition compared with the DT-paper and DT-phone. Based on the short-term LyE, we conclude that smart glasses may have more limited adverse effects on stability compared with the paper-based system or smartphone. It is also worth noting that the display conditions tested here only had significant effects on λ_s, but not λ_L. These results are perhaps not surprising, though, as prior studies have shown that the short-term LyE is an actual predictor of stability, but not the long-term LyE [29], and these two indexes may provide contradictory conclusions [30].

As mentioned earlier, participants adopted different head postures based on the walking conditions. During the head-down conditions (i.e., DT-paper and DT-phone), participants could see their feet while walking. As such, these head-down conditions provided more visual feedback regarding lower-limb positions. Perceiving and encoding this additional feedback could have increased attentional cognitive demands for the head-down conditions. Such increased cognitive demands in these conditions may explain why the DT-paper and DT-phone conditions were more disturbing than the ST and DT-glass conditions.

There are some limitations associated with the current study. First, we quantified local stability based on the time series of the C7 marker. Different head postures (i.e., head-down and head-up postures) may affect the positions of the C7 marker, and consequently, the LyE results.

We completed additional analyses, however, which indicated that the LyE results for the C7 marker were similar to those for a lower maker (i.e., T10). We only reported results here for the C7 marker, because raw data for this marker had a higher quality (in terms of noise) compared to T10. We also placed the C7 marker directly on the skin, whereas the T10 marker was on the participants' shirts, which increased errors in our calculations. Another potential confounding factor in evaluating the risk of falls in this study is that the participants may have prioritized walking performance (i.e., maintaining walking goals) over cognitive performance. As we noted earlier [12], we included a seated cognitive condition at the beginning each experimental session. In this condition, participants performed the same cognitive tasks that they needed to complete during the dual-task activities. Overall, participants had similar or slightly better performance during the dual-task conditions compared with the seated task. These results suggest that the participants did not need to sacrifice cognitive performance to maintain the constant walking speed. It is also worth noting that there are not any standard procedures for analyzing nonlinear time series, and those previous studies have used different algorithms and parameters. The procedures we used here for measuring LyE were based on a seminal and well recognized study. However, future work should be done to develop standard methods for measuring LyE. Finally, there are different types of smart glasses, and we do not know to what extent we can generalize these results for the other types.

In summary, using smart glasses appeared to have more limited adverse impacts on gait performance (e.g., stability and gait variability) compared to other information displays. On the other hand, this relatively new technology disturbed the control of important gait variables (e.g., lateral position), which may be due to participants' lack of experience in using the smart glasses. Based on these results, we conclude that, while smart glasses may be a safer alternative for information presentation than other approaches, they are not ready to be implemented in practice. We also suggest that designers should consider different gait variables, especially lateral position, for evaluating the design of such new technologies and for assessing dual-task gait conditions.

Declaration of Competing Interest

None.

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