A robotic system for delivering novel real-time, movement dependent perturbations

Zrinka Potocanac[a], Rok Goljat[a], Jan Babic[a]

[a]Department for automation, biocybernetics and robotics, Jozef Stefan Institute, Jamova cesta 39, Ljubljana, Slovenia

E-mail addresses:

Zrinka Potocanac	zrinka.potocanac@ijs.si
Rok Goljat	rok.goljat@ijs.si
Jan Babic	jan.babic@ijs.si

Corresponding author:

Zrinka Potocanac

Department for automation, biocybernetics and robotics, Jozef Stefan Institute, Jamova cesta 39, 1000 Ljubljana, Slovenia

e-mail: zrinka.potocanac@ijs.si, zpotocanac@gmail.com

Acknowledgements

The authors would like to thank Dasa Gorjan for help with the ac- quisition of human quiet standing data and Jernej Camernik for ren- dering Figs. 1 and 2A. This work was supported by the European Union’s Horizon 2020 through projects SPEXOR (contract no. 687662) and AnDy (contract no. 731540) and by the Slovenian Research Agency (research core funding no. P2-0076). None of the funding sources had any involvement in this research.

Introduction

Balance is often studied by investigating responses to perturbations and one of the most common experimental paradigms to elicit perturbations involves the participant standing on a moving platform [1–6]. Such experiments mostly use discrete perturbations consisting of simple platform translations [1–3,5,7], although some studies use more complex perturbations [4,6,8]. However, all of the abovementioned studies use perturbations defined prior to the experiment, which remain constant throughout. Such perturbations are representative of external disturbances to balance and the underlying research is often aimed at fall prevention. However, the largest proportion of falls is not due to an external disturbance. Namely, 41% of falls is attributed to incorrect weight shifting [9], probably reflecting self-generated movement errors. Indeed, a link between falling and errors in weight shifting is strengthened by studies showing that errors in weight-shifting during step initiation are especially likely in the elderly [10] and delay foot lift-off [11], which is a predictor of future falling [12]. Hence, it is important to study self-generated weight shifting errors; for which novel perturbation paradigms are needed. Our aim was to create a system that can induce novel perturbations proportional to one's own center of mass (COM) movement with minimal delays. Such perturbations are inspired by self-generated weight shifting errors, since they add a systematic error to the whole movement, as opposed to a predefined error occurring at a specific time point. We present sophisticated, real-time, movement-dependent perturbations delivered by a closed-loop system consisting of a robotic platform moving in response to real-time COM displacements of the subject standing on top of it. The performance of this system is evaluated in terms of accuracy of the generated perturbation and its delay relative to the input signal (i.e., the COM kinematics). Additionally, we show that such perturbations induce increased postural sway in young adults (YA) during a simple task of quiet stance.

Methods

Technical implementation

A six degree of freedom Stewart platform [13] was controlled in real-time by a custom made Matlab Simulink 8.6 model (Mathworks, Natick, USA). The control model duplicated the participant's COM displacement online by moving the platform in the opposite direction, based on real-time input from a kinematic marker positioned at L5. The kinematic data were sampled at 100 Hz, and the Simulink Model ran at a 1000 Hz, resulting in millisecond control of the Stewart platform. Platform movements were limited to mediolateral (ML) translations in response to ML COM displacement. Technical details of the system are provided in Fig. 1. and supplementary material.

Experimental procedures

We evaluated the performance of the perturbation in terms of delays and accuracy. Delivering a movement-dependent perturbation consists of two stages: processing, reflecting the input signal acquisition and calculation of the appropriate perturbation, and execution, reflecting platform movement once a perturbation has been calculated. We evaluated these separately. First, we used a predefined perturbation waveform as the input to platform movement and evaluated the execution phase, i.e., the mechanics of the system. Second, we used ML COM displacement of healthy YA as input to create ML movement dependent perturbations and evaluated the overall system performance, comprising both the processing and execution. In both cases, we calculated the cross-correlation between the input signal and platform movement and evaluated accuracy, defined by the maximal correlation coefficient and delay, defined by the corresponding lag. The execution phase was defined by the lag and correlation between measured platform movement and the predefined perturbation waveform. Overall performance was defined by lag and correlation between measured ML platform and COM movements of YA during quiet stance, averaged over participants.

Fifteen healthy YA (mean ± SD: age 24.1 ± 3.3 years, height 174.1 ± 7.6 cm, weight 70.2 ± 9.6 kg, 8 females) participated in this experiment after signing informed consent. Participants were instructed to stand as still as possible with their eyes closed, the feet hip-width apart and the arms relaxed by their body. The task was performed from the same starting position with the platform off and on for at least 175 s. We truncated the first 45 s of data, detrended the data and used the subsequent 30 s for our calculations. Kinematic data were recorded at 100 Hz, using a 1x3 Optotrak camera array (Northern Digital Inc., Waterloo, Ont., Canada) from markers positioned on the platform and the participant at the L5 level.

Finally, to asses the effect of the perturbation on postural sway, we calculated the range and SD of the COM movement relative to the platform and its mean power frequency (MPF) [14]. Data were compared between the platform on and off conditions using Wilcoxon signed rank test, with $\alpha = 0.05$.

All analyses were performed using MATLAB 2015 (Mathworks, Natick, USA) and SPSS Statistics 21 (IBM, Chicago, IL, USA).

Results

Performance of the perturbation setup

Figure 2 shows the perturbation movement generated by a predefined perturbation (Fig. 2A) and by postural sway of a representative participant (Fig. 2B). The support surface movement accuracy was high in both situations, as shown by correlation coefficients of 0.99994 and -0.984, for execution and overall performance, respectively. Delays in platform movement were 150 ms and 154 ms (range 120 – 170 ms), for execution and overall performance, respectively.

Effect of the perturbation on postural sway

The platform perturbation significantly affected ML sway, as shown in Fig. 3. With the perturbation on, ML range increased from 5.56 ± 3.72 to 9.58 ± 4.83 mm ($p = 0.01$), SD increased from 1.08 ± 0.74 to 1.72 ± 0.74 mm ($p = 0.02$), and MPF increased from 0.08 ± 0.05 to 0.25 ± 0.17 Hz ($p < 0.01$). We found no statistically significant differences in the AP values (range 15.02 ± 5.57 and 17.66 ± 7.60 mm, SD 3.36 ± 1.20 and 4.01 ± 1.65 mm, MPF 0.11 ± 0.05 and 0.09 ± 0.05 Hz, with the platform off and on, respectively).

Discussion

We described a system which delivers novel online, movement dependent perturbations in response to COM movements. Using this system, we induced perturbations that doubled the COM movement with an average delay of 154 ms, which is short enough for participants not to detect the delay [15] and around the latency at which YA judge that 50% of delayed movements exactly correspond to their own, when explicitly asked [16]. This delay is mostly due to electromechanical limitations of moving the Stewart platform (e.g., inertia and delays

in robotic motor controllers) and we are currently developing motor controllers to reduce it further.
This perturbation induced increased sway range, variability, and frequency with respect to the platform movement in healthy YA, indicative of a change in postural control strategy (e.g., increased frequency of postural sway was previously associated with stiffening in threatening conditions [14] or more automatic/tighter postural control when attention is diverted [17–19]). In this experiment, we limited our perturbations to ML direction, but our system is modular and perturbations in all directions, including support surface rotations, can be induced, based on kinematic input signals of markers positioned at any anatomical landmark.

In conclusion, we provide a novel systematic, movement dependent perturbation inspired by self-generated weight shift errors. We hope this will contribute to a better understanding of the mechanisms underlying balance and whole body movement control.

References

1. Nonnekes JH, Scotti A, Oude Nijhuis LB, Smulders K, Queralt A, Geurts ACH, Bloem BR, Weerdesteyn V. Are postural responses to backward and forward perturbations processed by different neural circuits? Neuroscience 2013; 245: 109–20
2. McIlroy WE, Maki BE. Task constraints on foot movement and the incidence of compensatory stepping following perturbation of upright stance. Brain Res. 1993; 616: 30–8
3. Jacobs J V, Horak FB. External postural perturbations induce multiple anticipatory postural adjustments when subjects cannot pre-select their stepping foot. Exp. Brain Res. 2007; 179: 29–42
4. Joseph Jilk D, Safavynia SA, Ting LH. Contribution of vision to postural behaviors during continuous support-surface translations. Exp. Brain Res. 2014; 232: 169–80
5. Welch TDJ, Ting LH. Mechanisms of motor adaptation in reactive balance control. PLoS One 2014; 9: e96440
6. Van Ooteghem K, Frank JS, Allard F, Buchanan JJ, Oates AR, Horak FB. Compensatory postural adaptations during continuous, variable amplitude perturbations reveal generalized rather than sequence-specific learning. Exp. Brain Res. 2008; 187: 603–11
7. Welch TDJ, Ting LH. A feedback model reproduces muscle activity during human postural responses to support-surface translations. J. Neurophysiol. 2008; 99: 1032–8
8. Maurer C, Mergner T, Peterka RJ. Multisensory control of human upright stance. Exp. Brain Res. 2006; 171: 231–50
9. Robinovitch SN, Feldman F, Yang Y, Schonnop R, Leung PM, Sarraf T, Sims-Gould J, Loughin M. Video capture of the circumstances of falls in elderly people residing in long-term care: an observational study. Lancet 2013; 381: 47–54
10. Sparto PJ, Fuhrman SI, Redfern MS, Perera S, Jennings JR, Furman JM. Postural adjustment errors during lateral step initiation in older and younger adults. Exp. Brain Res. 2014
11. Sparto PJ, Fuhrman SI, Redfern MS, Jennings JR, Perera S, Nebes RD, Furman JM. Postural adjustment errors reveal deficits in inhibition during lateral step initiation in older adults. J. Neurophysiol. 2013; 109: 415–28

12. Lord SR, Fitzpatrick RC. Choice stepping reaction time: a composite measure of falls risk in older people. J. Gerontol. A. Biol. Sci. Med. Sci. 2001; 56: M627-32

13. Stewart D. A platform with six degrees of freedom. Arch. Proc. Inst. Mech. Eng. 1847-1982 (Vols 1-196) 1965; 180: 371–86

14. Carpenter MG, Frank JS, Silcher C, Peysar G. The influence of postural threat on the control of upright stance. Exp. Brain Res. 2001; 138: 210–8

15. Blakemore SJ, Frith C. Self-awareness and action. Curr. Opin. Neurobiol. 2003; 13: 219–24

16. Franck N, Farrer C, Georgieff N, Marie-Cardine M, Dal??ry J, D'Amato T, Jeannerod M. Defective recognition of one's own actions in patients with schizophrenia. Am. J. Psychiatry 2001; 158: 454–9

17. Richer N, Saunders D, Polskaia N, Lajoie Y. The effects of attentional focus and cognitive tasks on postural sway may be the result of automaticity. Gait Posture 2017; 54: 45–9

18. Stins JF, Roerdink M, Beek PJ. To freeze or not to freeze? Affective and cognitive perturbations have markedly different effects on postural control. Hum. Mov. Sci. 2011; 30: 190–202

19. Zaback M, Carpenter MG, Adkin AL. Threat-induced changes in attention during tests of static and anticipatory postural control. Gait Posture 2016; 45: 19–24

Conflict of interest statement

None.

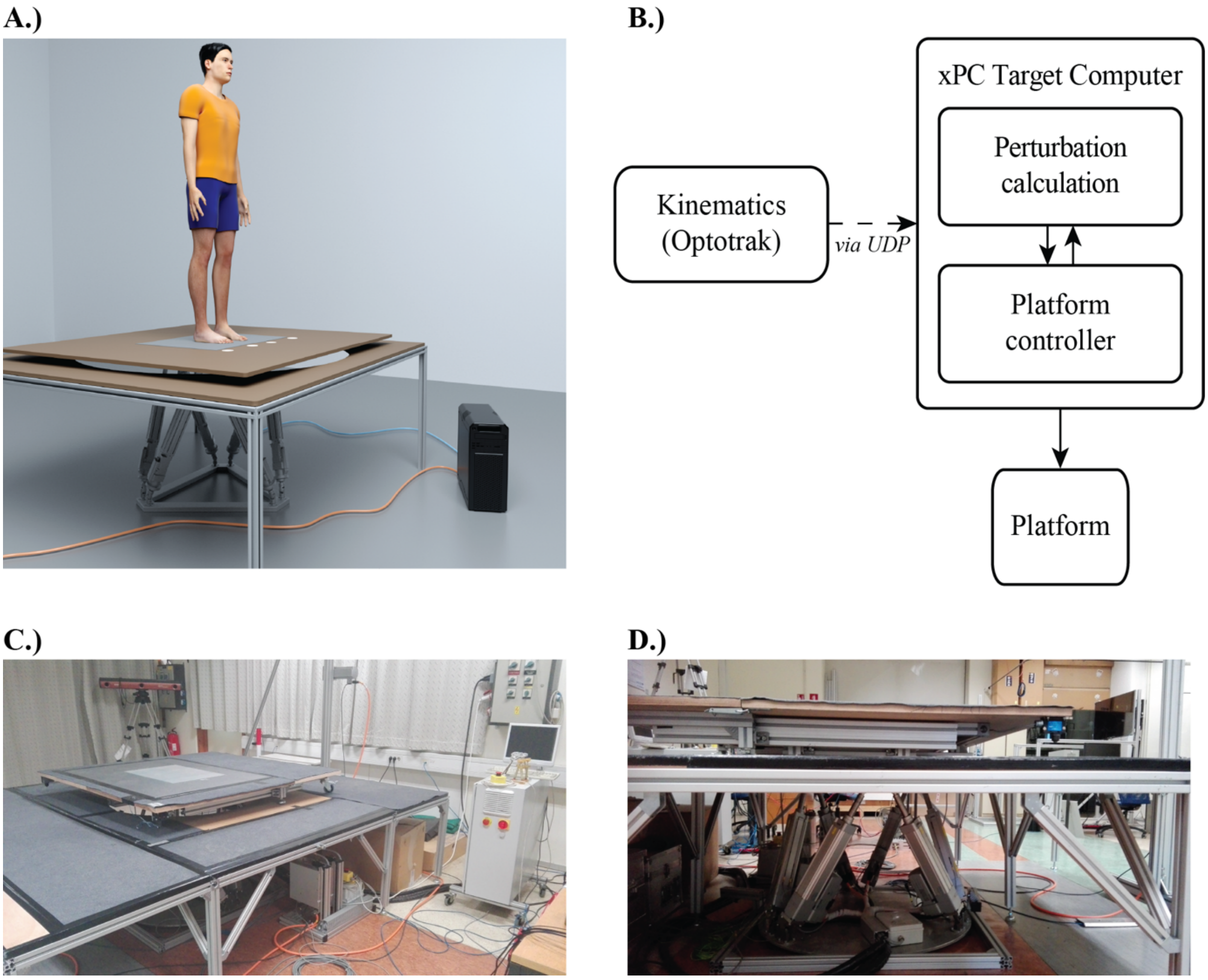

Figure 1. Schematics of the hardware (A) and the software (B), top (C), and side (D) views of the perturbation setup. On top of a six degree of freedom Stewart platform, we mounted two force plates (Kistler Instrumente AG, Winterthur, Switzerland), embedded within a larger wooden plate covered by a carpet. This created a moveable support surface of 1.5 x 1.5 m. For safety, we surrounded the support surface by a non-moveable wooden plateau (2.5 m x 3 m) and equipped it with safety switches that would arrest any movement in case it touched the wooden plateau. Hence, our participants stood on a moveable support surface 17 cm above a fixed and stable wooden plateau. The Stewart platform was controlled in real-time by a custom made Matlab Simulink 8.6 model (Mathworks, Natick, USA), which aimed to double the ML COM displacement by a corresponding ML platform translation in the opposite direction. For safety reasons, the platform displacement was defined for each time sample (1 ms) as the average of the COM displacement in the last four time samples (4 ms) and limited to max 7 mm/ms. We used a kinematic marker positioned at the L5 as input to the control model, which ran in real-time on an xPC Target (Mathworks, Natick, MA, USA). xPC Target is a solution that allows running the model on a dedicated "target" computer. This computer is booted with the xPC Target real-time kernel and its hardware is completely dedicated to xPC Target tasks, therefore achieving hard real-time performance. We sampled the kinematic data at 100 Hz, and ran the Simulink Model at 1000 Hz. Note that we limited platform movements to mediolateral translations in response to mediolateral COM displacement, but with a different Matlab Simulink model, the system would be able to produce support surface translations and tilts in all directions based on input from a marker placed at any anatomical landmark. Additional detail of the technical implementation can be found in the supplementary material.

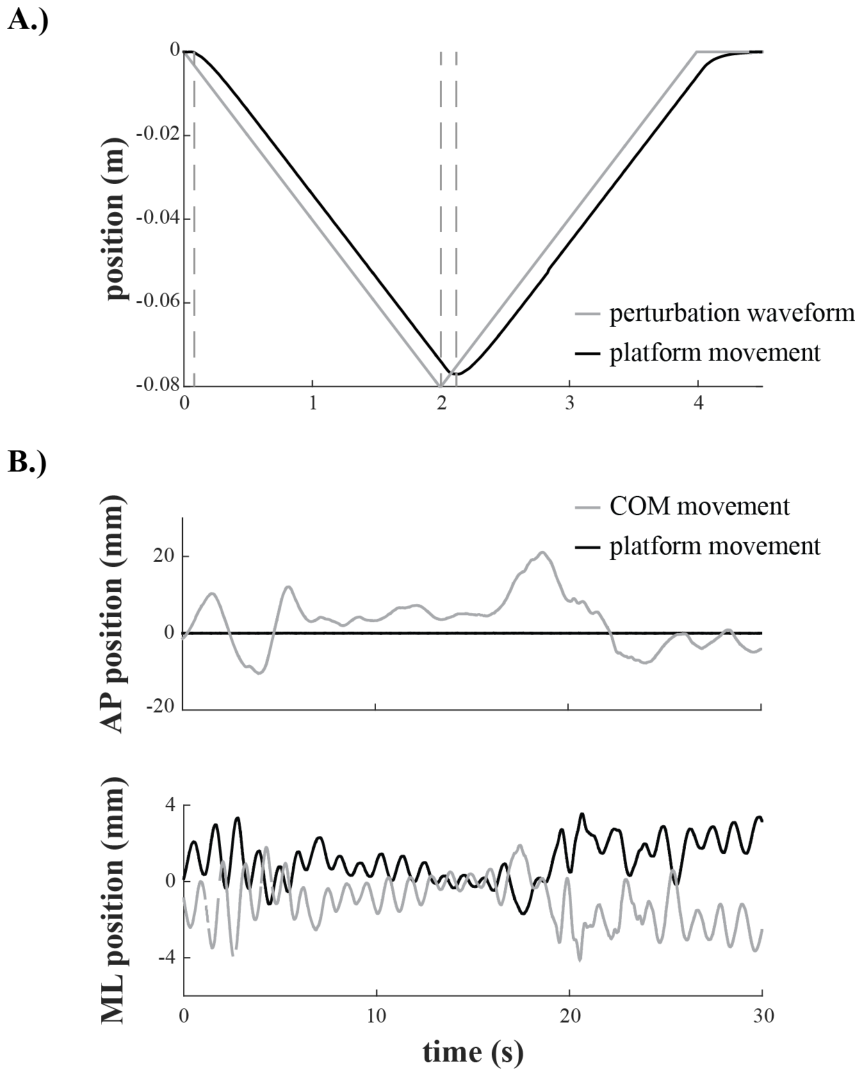

Figure 2. Execution (A) and overall (B) performance of the perturbation setup. (A) A predefined perturbation waveform and the corresponding platform movement illustrate the execution phase performance, i.e., the mechanics of the system. (B) ML COM displacement was used as input to create ML movement dependent perturbations, illustrating the overall system performance. Data of a representative subject (subject # 7) are shown. COM = center of mass, ML = mediolateral, AP = anteroposterior.

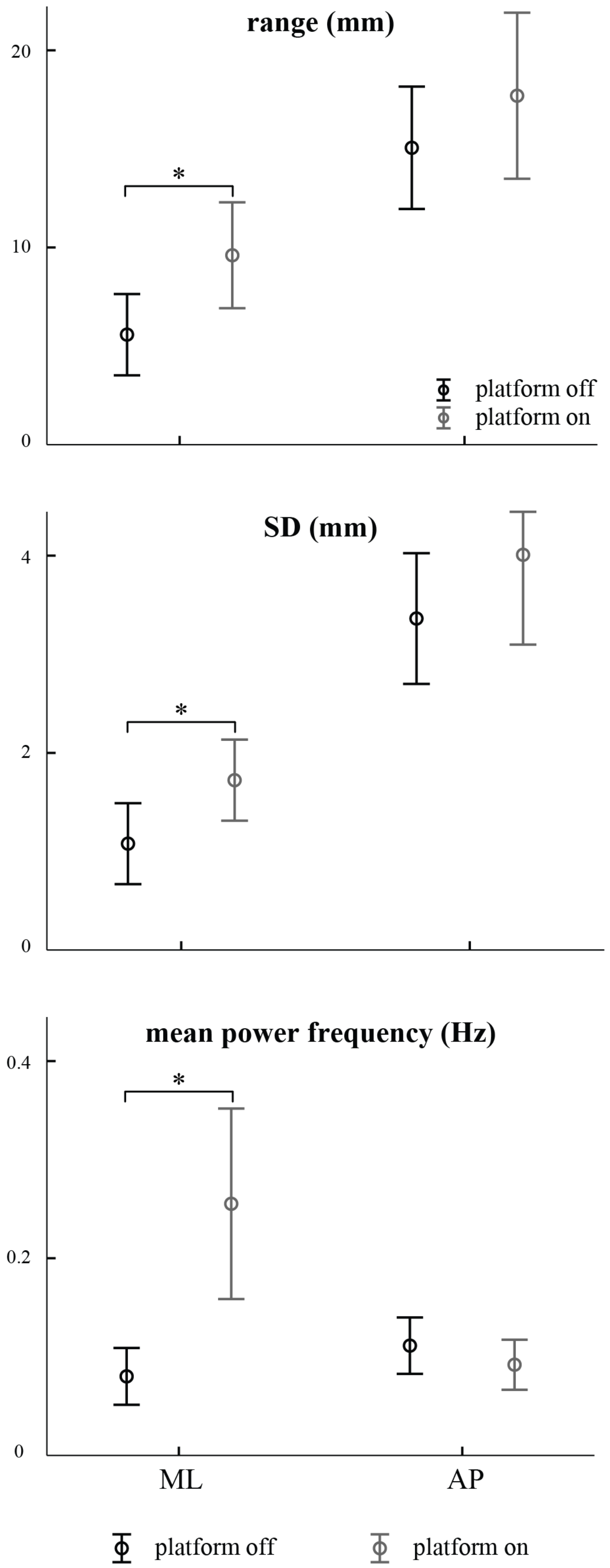

Figure 3. Effects of the perturbation on human motor control during quiet stance with eyes closed. Error bars indicate 95% confidence intervals; statistically significant differences are indicated by an asterisk. SD = standard deviation, ML = mediolateral, AP = anteroposterior.