Natural control of a lower-limb exoskeleton: using upper-body kinematics to detect gait initiation intention

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I. Background

Over the last few decades, medical lower-limb exoskeletons have emerged from various research teams and private industrials to serve as assistive or rehabilitation devices [1]. While still facing many challenges regarding their development and design, these robotic structures show promising results for being used in real-world settings, and allow either safe ambulation of people suffering from lower-limb impairments [2].

One key aspect in the development of lower-limb exoskeletons is their ability to be perceived as integrated parts of the users' bodies [3]. However, in order to achieve such an integration, it is important to provide correct interfacing with the users' sensory-motor control system and to properly convey movement intentions through natural and intuitive control strategies. Most marketed devices rely on constraining interfaces based on external inputs or the execution of predefined movements to trigger different walking states [4], [5]. But knowledge on human motor control and the analysis of specific body motions can be exploited to build more intuitive and robust interfaces. In particular, the natural kinematic coordination between different parts of the body during gait events can exhibit predictive patterns, such as the anticipatory postural adjustments (APAs) that appear during gait initiation [6]. With the use of machine learning and pattern recognition techniques, it is possible to properly identify such patterns in unimpaired individuals in a free walking setting based on inertial measurements [7].

In recently published work, we showed that similar patterns still exist when unimpaired individuals have their legs constrained by a lower-limb exoskeleton, and can be successfully used within a supervised classification architecture to trigger the robot's walking state with minimal false positive rates [8].

II. Methods

The protocol was designed to evaluate the implementation of a classification architecture to correctly detect gait initiation intention in an exoskeleton based on upper-body inertial measurement unit (IMUs) signals, and assess its robustness against false positive detections. This experimental framework is detailed in Fig.1.

In a first experiment, IMUs were used to record arm and back movements from ten participants as they performed 20 trials of 4 m walks in a free unconstrained setting (FS condition). Data from this condition were then labeled and used as training sets for a Linear Discriminant Analysis (LDA) classifier [9]. The classifier was trained to distinguish between four classes: No Movement (NM), Gait Initiation Intention (GII), Left Step (LS), and Right Step (RS). The participants were then placed in the Atalante exoskeleton developed by the Wandercraft company (bottom right of Fig.1) and were asked to perform whatever upper-body movements they thought would initiate the robot's walking state over 20 trials. During this Constrained Setting (CS) condition, the classifier was used to evaluate the possibility of correctly triggering the exoskeleton based on different FS data training sets (individual data from the tested participant, data from all other participants, or data from all 10 participants). Two participants didn't correctly follow the protocol and were discarded from the CS condition analyses.

In a second experiment, eight of the ten participants wore the IMUs in the exoskeleton, and were asked to perform a set of typical everyday movements with each arm. Data from this experiment were used to enrich the training sets for the classification architecture by adding an extra Miscellaneous Movements (MM) class, and tested offline on data from the CS condition of Experiment 1.

III. Results and Conclusion

Data from the FS condition were consistent with previous APA studies, and showed that before heel-off, the trunk is accelerated forwards, and towards the standing leg [6]. They also showed that both arms follow similar acceleration patterns, and exhibit predictive movements, with a delay between the arm ipsilateral to the stepping leg – which starts moving first – and the contralateral arm. An offline implementation of the classifier showed that for all subjects and during all trials, the Gait Initiation Intention (GII) class was always correctly detected.

Data from the CS condition showed that the participants actively engaged in using the upper-body side ipsilateral to the stepping leg when initiating gait, and naturally exhibited patterns similar to the FS condition (upper middle box in Fig.1). However, forward acceleration phases were shorter and of lower amplitude, followed by high amplitude decelerations. Angular velocities were also higher in both the antero-posterior and medio-lateral planes, confirming that participants actively rotated their upper-body laterally, and bringing it forwards, while bringing the ipsilateral arm towards the standing leg.

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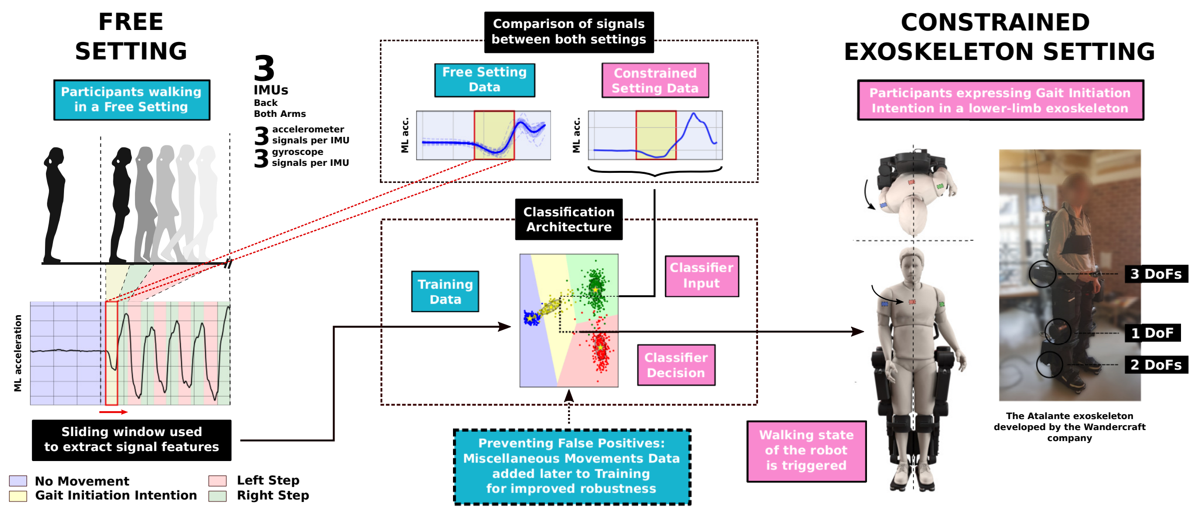

Fig. 1. The experimental framework of the study. The first experiment was divided into two conditions: the Free Setting (FS) condition in which participants walked in an unconstrained setting, and the Constrained Setting (CS) condition in which participants expressed gait initiation intention in a lower-limb exoskeleton using their upper body. Signals from both settings were compared to assess the reproducibility of predictive patterns between the two conditions (standardized medio-lateral (ML) accelerations represented here), and a classification architecture was implemented based on the FS data to detect gait initiation intention in the CS condition. Additional data from the second experiment were used to improve the robustness of the classifier.

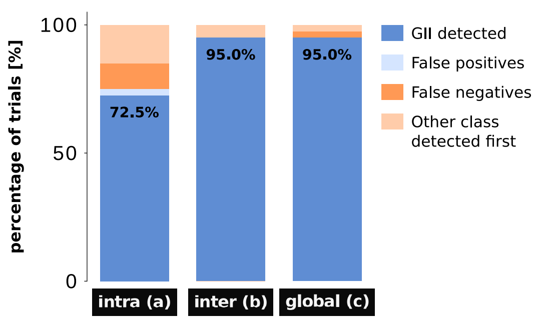

Fig. 2. Results of the classification during the CS condition during gait initiation for each training set. The intra training set was based on individual data from each participant during the FS condition, the inter training set was based on data from all participants except the tested one, and the global training set was based on data from all participants.

The classification architecture was successfully used during the CS condition to detect gait initiation intention in 95% of the trials where data from all participants were used in the training set (Fig.2). This confirms that participants intuitively engaged in a similar movement strategy that is close to the FS condition patterns.

However, analysis of the Experiment 2 data using this same classifier showed that everyday movements were prone to induce false positive detections of Gait Initiation Intention. By including part of these data in the classification training set, the rate of false GII positives in Experiment 2 was reduced from 27.6% to 1.5%. This enriched set was then tested offline on data from the CS condition, and showed that the GII class could be successfully detected in all trials but one, confirming the increased robustness of the classification architecture used to detect the users' intention.

This work shows a promising way to build more intuitive control interfaces for lower-limb exoskeletons based on the analysis of natural movements exhibited in free unconstrained settings. However, the predictive patterns used here were analysed based on unimpaired subjects data, and further experimentations need to be conducted with participants suffering from mobility disorders to assess the transferability of these methods to more realistic use cases of exoskeletal devices.

References

[1] W. Huo, S. Mohammed, J. C. Moreno, and Y. Amirat, "Lower Limb Wearable Robots for Assistance and Rehabilitation: A State of the Art," *IEEE Systems Journal*, vol. 10, no. 3, pp. 1068–1081, 2016.

[2] L. E. Miller, A. K. Zimmermann, and W. G. Herbert, "Clinical effectiveness and safety of powered exoskeleton-assisted walking in patients with spinal cord injury: systematic review with meta- analysis," *Medical Devices: Evidence and Research*, 2016.

[3] W. Seymour, *Remaking the Body*. Routledge, feb 1998.

[4] A. Esquenazi, M. Talaty, A. Packel, and M. Saulino, "The Rewalk powered exoskeleton to restore ambulatory function to individuals with thoracic-level motor-complete spinal cord injury," *American Journal of Physical Medicine and Rehabilitation*, vol. 91, no. 11, pp. 911–921, 2012.

[5] K. A. Strausser and H. Kazerooni, "The development and testing of a human machine interface for a mobile medical exoskeleton," *IEEE International Conference on Intelligent Robots and Systems*, pp. 4911–4916, 2011.

[6] Y. Brenière and G. Dietrich, "Heel-off perturbation during gait initiation: biomechanical analysis using triaxial accelerometry and a force plate." *Journal of biomechanics*, vol. 25, no. 2, pp. 121–7, feb 1992.

[7] P. Rebersek, D. Novak, J. Podobnik, and M. Munih, "Intention Detection During Gait Initiation Using Supervised Learning," in *2011 11th IEEE-RAS International Conference on Humanoid Robots*, 2011, pp. 34–39.

[8] O. M. Alaoui, F. Expert, G. Morel, and N. Jarrassé, "Using generic upper-body movement strategies in a free walking setting to detect gait initiation intention in a lower-limb exoskeleton," *IEEE Transactions on Medical Robotics and Bionics (Early Access)*, 2020.

[9] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*, ser. Springer Series in Statistics. New York, NY, USA: Springer New York Inc., 2001.