Proceedings of the 5th International Conference on Modern Medicine and Global Health
DOI: 10.54254/2753-8818/2027.39067

Perception and Trajectory Coordination During Terrain Transitions in Lower-Limb Exoskeletons

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Abstract. The use cases for lower limb exoskeletons are moving from controlled indoor conditions (e.g., treadmill) to challenging outdoor conditions. Terrain changes, such as ramps, compliant surfaces, steps, and curbs, change swing-leg clearance, foot placement, stance-phase duration, and joint torque requirements, making prerecorded fixed trajectories difficult to adjust to these changes. Smooth terrain transitions rely on the ability of the look-ahead perception, wearable sensing, and foot–ground contact-state estimation to provide information for decision-making in the planning process prior to critical contact events and to be converted into continuously executable reference trajectories. In this regard, a review of the literature on terrain perception, gait decision making and trajectory transition is presented and approaches are categorized into fixed-trajectory replay, rule-based switching, and closed-loop adjustment based on the way environmental information is fed into the planning layer. Current research suggests that terrain adaptability is not only related to single perception or control modules, but also to the coordination between the updating of perception, the switching time, and the continuity of the trajectory. Lastly, current difficulties and future research directions are discussed for perception–control timing alignment, smooth trajectory transitions, the testing benchmarks, and failure recovery.

Keywords: lower-limb exoskeleton, terrain perception, gait decision-making, trajectory transition, adaptive control

1. Introduction

Terrain variation is a common occurrence in outdoor walking and includes ramps, compliant surfaces, steps and curbs. Lower-limb joint motion, time of foot strike and torque requirements change on uphill slopes, soft surfaces and steps [1, 2]. For example, compliant ground has lower contact stiffness, and multi-terrain tests of ankle exoskeletons have also found greater deviations in ankle kinematics on softer surfaces [2]. Steps and curbs, meanwhile, require swing-leg clearance and foot placement to be adjusted to the terrain. So, swing height, foot position, stance time and demands for output of the joints all change with the terrain. Multiple ground conditions are not easily covered by a single predefined trajectory, and an exoskeleton should therefore gain insight into a ground condition and adapt its reference motion for the next critical contact event.

In this paper, the related work is grouped into three categories according to the way that environmental information is incorporated into the planning layer [3, 4]. The first is fixed-trajectory

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DOI: 10.54254/2753-8818/2027.39067

replay: the controller replays prerecorded or offline-optimized joint-angle profiles over time, and the planning layer does not change the reference according to the terrain. The second is rule-based switching: terrain classes are calculated from sensor measurements, and the controller switches among a few known gaits. Environmental information is introduced into decision-making as discrete modes; the number of modes is limited, and the switching conditions are usually determined manually. The third is closed-loop adjustment: terrain parameters are estimated using look-ahead perception; body and contact states are measured by wearable and plantar-force sensors; the decision module transforms the parameters into gait strategies; and the trajectory generator adjusts the joint-angle or torque reference. Past reviews have categorized trajectory-planning strategies in controlled laboratory settings and open, real-world environments [5]. In contrast, this paper structures the discussion according to how environmental information is integrated into the planning layer, with a focus on coordination among modules.

There is a great variety of studies with respect to sensor placement, camera frame rate, control frequency, gait pattern, terrain categories, and switching timing. Some only give the accuracy in terrain classification, others only trajectory-tracking errors. Therefore, a single module's metrics would not be able to determine if perception results are translated to executable trajectories in time. This paper takes into account inter-module coordination in the cross-study comparison, particularly definition of terrain, prediction lead time and end-to-end latency, continuity when switching trajectories and actuator and wearer conditions. While a lot of terrain classification studies are able to reach very high recognition accuracy, few studies explain in detail how and when the results of terrain classification enter the controller [6]. It has been shown by benchmarking that overall accuracy of gait-event detection decreases as the terrain becomes more complex [7]. Thus a good score on single metrics cannot be guaranteed to provide reliable adaptability to terrain for the overall system.

The roles and timing requirements of the look-ahead terrain information, the wearable state information and the contact events at the terrain transitions are first explored. It then discusses the comparison between rule-based switching, closed-loop trajectory adjustment and smooth transition methods. Finally, it gives an overview of existing problems and future research directions in the areas of perception–control timing, continuous terrain representation, testing benchmarks and failure recovery.

2. Terrain information and gait adjustment requirements

Images of the ground ahead of the foot are captured by depth or red-green-blue cameras. After classification or geometric analysis, parameters such as terrain class, slope angle, step height, and tread depth are obtained [6]. This information provides prediction lead time: a reference trajectory can be modified only if the information reaches the controller before the relevant terrain contact. Classification speed alone does not determine usable lead time. Terrain acquisition during walking depends on the camera mounting location and viewing distance, while processing and adjustment delays depend on computational latency and walking speed. All four factors must therefore be considered together.

Wearable and contact-state information is provided by inertial measurement units, joint encoders, and plantar force sensors which inform on body posture, gait phase, and current contact state. IMU-based gait-event detection has been systematically evaluated on diverse terrains and the output may be used to assist the decision module to switch between gaits [7]. These signals, unlike the look-ahead information, change quickly and are not lighting dependent. However, they only indicate terrain changes when they are close or after contact, and as such have limited lead time in most

DOI: 10.54254/2753-8818/2027.39067

circumstances. The two sources are thus complementary, look-ahead perception estimating terrain of the next step, and wearable and contact sensors confirming body and contact states.

There exist 2 different representations of terrain states. One is based on discrete categories, e.g., level ground, uphill slopes, stairs, which can be easily selected from a set of predefined strategies, but may result in decision jitter at the boundaries between categories. The other is based on continuous parameters such as slope angle, ground stiffness, and elevation difference, which can directly affect gait parameters and provide temporally smoother results, but at the expense of a dependence on accuracy and delay of estimation. Each representation has appropriate applications and influences the downstream decision making and trajectory-generation architecture.

All three types of information have timing requirements. The visual perception system has a frame rate and image processing time, which limit its ability to update as often as the low level control loop. Contact and event estimates can be quicker - but only for the current step. Out-of-sync terrain information, gait phase, and trajectory updates could cause the controller to make decisions based on stale data. Table 1 summarizes the content and timing characteristics of the information sources.

Table 1. Information sources and timing characteristics during terrain transitions

Information source	Information provided	Timing characteristics
Look-ahead vision	Terrain class, slope, step geometry	Provides lead time; update rate limited by frame rate
Wearable IMU	Gait phase, event timing	Fast updates; mainly reflects current state
Plantar force	Contact state, load distribution	Fast updates; available only after contact

Table 1 highlights the complementary timing characteristics of the sensing modalities. Look-ahead vision can provide an opportunity to adjust the following step before contact; its usable lead depends on the camera, frame rate, processing delay, and walking speed. Wearable inertial measurement unit (IMU) and plantar-force measurements provide more frequent updates that verify the current gait and contact state, but they cannot substitute for prior knowledge of an approaching obstacle or slope. Therefore, a terrain-transition decision should consider when an estimate is produced and which event in the gait cycle it can still affect.

3. Decision-making and trajectory transitions

3.1. Fixed trajectories and rule-based switching

Baselines to understand closed-loop approaches include fixed-trajectory replay and rule-based switching [3, 4]. Low-level servo tracking is still typically based on position or torque feedback, and the planning layer does not include updates based on the environment in fixed-trajectory replay. The reference curve set once recorded cannot be changed. The reference trajectory does not adapt to the environment if out of the calibration conditions.

Rule-based switching adds terrain judgment to fixed-trajectory control. The system, for instance, can transition from a flat ground mode to an uphill mode, if it determines that the slope is too steep, or determine the stiffness of the ground by measuring changes in the plantar force. Multimodal wearer signals may also be used to inform mode selection as a result of motion-intention recognition [8]. This way offers a simple way to react to the environment, with two issues in mind. The first is

DOI: 10.54254/2753-8818/2027.39067

jitter near thresholds: sensor measurements have noise and the parameters of terrain fluctuation around a threshold may cause frequent switching between modes. The second is that there might be a discontinuity at the transition. When the predefined modes are not coordinated by joint angle, joint velocity, or torque, the reference may jump at the switching instant, and the output can change abruptly. Additionally, the two trajectories can be off phase at the switching point, interfering with the subsequent steps' rhythm.

3.2. Closed-loop trajectory adjustment

Closed-loop approaches differ according to how feedback is used to adjust gait parameters.

The terrain-classification-based approach is used to determine the category of terrain and then change the pre-determined parameters. In this category, the rhythmic signal sources, called central pattern generators (CPGs), are often encountered and can generate coordinated periodic signals for several joints. Once the terrain classification results are input into the CPG, phase offsets, amplitudes or frequencies are adjusted to reflect the new terrain. In some studies, CPG is not only used as a trajectory planner, but is also used as a controller, which directly outputs the signals for action and adaptively corrects the output based on tracking error [9]. While these approaches have a clear structure, they are sensitive to the accuracy of the classification upstream – when classification is not accurate, or when classification is delayed, phase errors can be carried over joints and affect cooperation over the subsequent steps.

The second type directly maps continuous terrain parameters and body states to trajectory parameters or body actions, without explicitly classifying the terrain. While reinforcement learning can learn the mapping from terrain information to actions, it typically needs a lot of training data and the interpretability of policies and validation of safety is not easy. Model predictive control (MPC) is able to solve a short horizon optimization problem online, where the terrain parameters are considered as part of the constraints or cost function and trajectories or control commands are continuously optimized. However, it is very demanding in terms of computation and demands the necessary accuracy of the model and the speed of the solution. In the recent studies, these generation and adjustment methods have been systematically reviewed [4, 5].

Continuous parameter modulation and online optimization can help reduce the reliance on a small number of predefined trajectories and generate smoother reference outputs, as opposed to using a rule-based mode switching system. However, these methods can be effective under different conditions depending on the nature of the terrain, walking speed, perception latency, and control frequency and there is not yet a consistent quantitative comparison between different studies.

3.3. Continuity of trajectory transitions

There should be three levels of assessment for transition continuity. First, there are no step changes in the reference: the two predefined trajectories should have no step changes at the switching point (joint angles). Second, for continuous angle the angular velocity and acceleration should be evaluated for sudden changes which can also shock the actuator. Thirdly, actuator torque and foot–ground contact forces should be studied to identify sudden changes: torque jumps are directly transferred to the wearer, and sudden changes of the contact force may lead to a loss of balance.

One prerequisite for smooth transitions is knowing when the transition occurs. Prior research has used deep learning to recognize gait patterns and transition states simultaneously, with wearable-sensor evidence used to determine switching timing [10]. Phase-dependent interpolation, transition trajectories, or blending windows can blend old and new modes in stages when switching between

DOI: 10.54254/2753-8818/2027.39067

discrete categories. In the context of central pattern generators (CPGs), smooth transitions between rehabilitation phases have also been created with master-slave coupled oscillators to maintain phase continuity under disturbances [11]. If slope or elevation parameters vary continuously, trajectory parameters can be adjusted gradually with the environment without explicit switching. The important requirement is to define and guarantee continuity from recognition results to reference trajectories.

3.4. Decision-making and trajectory methods

The decision-making and trajectory-adjustment methods differ in how environmental information is incorporated into the reference trajectory and whether the transition is continuous, as summarized in Table 2.

Table 2. Decision-making and trajectory-adjustment methods for terrain transitions

Method	How environmental information is used	Trajectory output	Main limitations
Fixed trajectory	No real-time terrain information	Replays predefined trajectories by phase/time	Cannot adapt to unanticipated terrain changes
Rule-based mode switching	Triggered by terrain category or threshold	Switches among a limited set of predefined trajectories	Threshold jitter, limited modes, possible discontinuity at switching
Closed-loop: continuous parameter modulation	Continuous variables such as slope and height difference modulate gait parameters	Trajectory changes gradually with environmental parameters	Depends on accuracy and latency of continuous terrain estimates
Closed-loop: learning/ optimization-based online adjustment	Fuses terrain and body states to generate or correct trajectories online	Considers multiple variables and updates online	High demands for computation, data, interpretability, and safety validation

Table 2 shows a progression from methods that ignore real-time terrain information to dynamic references that depend on environmental and body states. Fixed replay provides a simple baseline, whereas rule-based switching can cause terrain-dependent chatter and discontinuities between modes. Continuous modulation and online learning or optimization provide more flexible adjustment, but they depend on estimation quality, computation time, and safety validation. These contrasts suggest that transition continuity and timely execution should be evaluated in addition to the chosen decision method.

4. Challenges and future directions

4.1. Timing mismatch between perception and control

The low-level control loop tends to run faster than visual perception. Therefore, the result of the visual perception may be stale by the time the perception result is available to the controller. The

DOI: 10.54254/2753-8818/2027.39067

accuracy of gait-event detection is also lower on more complicated terrains [7]. Therefore, by reporting classification accuracy, an evaluation of the usability of the perception result cannot be shown for the controller; in addition to the classification accuracy, the prediction lead time and the end-to-end latency must also be considered.

Future studies should consider an end-to-end latency evaluation of the perception–decision–trajectory chain and report the prediction lead time and processing time of each part consistently so that they can be compared to other studies. It should also explore how to compensate visual delay using high-frequency proprioceptive and plantar force inputs, how to add prediction to decision-making to improve lead time, and the applicability of these methods.

4.2. Bridging decisions and trajectories

Whilst joint trajectories, velocities and torques are continuous, many perception approaches report the presence of discrete categories like "step", "uphill" and "level ground". Misclassifications or repeated fluctuations near the boundaries of classification categories can result directly in trajectory discontinuities if each time the classification changes, another predefined trajectory is activated. Even if it is classified correctly, different positions of the switch during gait will result in different torques and foot-placement results. The fact of a change in terrain category should not be interpreted as a trajectory switch which happens instantaneously.

Future research should consider when to switch in addition to how to switch. The perception module might provide terrain-class confidence scores or continuous slope and height measures; the decision module might apply sustained confirmation or hysteresis; and the trajectory module might utilize phase-dependent interpolations, blending windows, or optimized transitions with angle, velocity and torque continuity constraints. Besides classification accuracy, experiments should present changes in angle, velocity, and torque at the switching instant and foot placement errors (to show that the changes in terrain judgments can be executed smoothly as gait changes).

4.3. Terrain benchmarks and cross-environment validation

Previous research has used a wide range of slope angles, step heights, surface materials, walking speeds, subjects, and sensor setups. Some studies provide information about only one laboratory surface, some provide only classification accuracy, and others provide only trajectory errors, making direct comparison difficult. Common real-world variations that are also often not included in validation are the illumination variation, occlusion, outdoor surface textures, slippery ground and compliant ground. Some studies have started employing standardized benchmarking for the performance of individual algorithms on real terrain and others have performed multi-terrain benchmark tests on whole exoskeleton systems [2, 7]. Automated public benchmarks, however, that span the perception–decision–trajectory pipeline are still few and far between.

In the future, a tiered testing protocol could be developed. The first stage would be the reporting of standardized level ground, ramps and steps for reproducible metrics. The second would involve tests of unseen slopes, unseen step heights, and varying walking speeds. The final stage would evaluate outdoor illumination changes, occlusion, and surface changes. The terrain recognition, end-to-end latency, trajectory-transition continuity, actuator saturation and safety events should be recorded in a consistent way for each experimental condition. Only standardized inputs and output metrics provide a meaningful way to compare different approaches.

DOI: 10.54254/2753-8818/2027.39067

4.4. Failure recovery and safety validation

In practice it is hard to rule out misclassification, dropped frames, and delayed information. There is relatively little information in the literature examined here on how the fallback strategy and recovery process work (e.g., reverting to a conservative gait or maintaining the current gait reference, and how many gait cycles are needed for recovery). Learning-based policies are also not easily interpretable, which adds to the challenge of safety assurance.

Further research may be done to test and confirm the stability of conservative fall-back and recovery operations through fault-injection experiments (misclassification, frame loss, delayed information, etc.). Traceable safety proof procedures also need to be studied to provide a clear experimental characterization of the range of operation of environmental perception approaches.

5. Conclusion

In this paper, the coordination of perception and trajectory generation during terrain transition in lower limb exoskeletons was studied. It surveyed the look-ahead terrain information, estimation of wearables, estimation of contact states, gait decision-making, and trajectory transitioning, and compared three different strategies: fixed-trajectory replay, rule-based switching, and closed-loop adjustment for environmental information entering the planning layer.

The literature analyzed shows that terrain recognition is but the beginning of the environmental adaptation pipeline. The proper timing of the gait transitions also requires that the information should arrive in time, that the decisions of the gait switches should be made correctly and in time, that the trajectories (joint-angle and velocity) should be continuous, and that the actuators should have the time to respond. Hence, classification accuracy cannot be used to assess overall terrain adaptability.

Current studies use a wide variety of terrain, walking speeds, sensor location, control frequencies, and evaluation metrics. The evidence remains mostly from individual modules or from controlled settings, and some evidence cannot be directly compared between studies.

In future research, the end-to-end latency should be standardized to evaluate the entire perception–decision–trajectory pipeline, including the prediction lead time and individual processing stage time. Gait-phase-aware transition mechanisms are also necessary to prevent abrupt changes in joint angles, joint velocities, and actuator torques at changes in terrain types. A tiered benchmark should include reproducible laboratory ramps, steps, and level surfaces, move to unfamiliar slopes, varying walking speeds, changing ground materials, occlusion, and walk outside the laboratory in outdoor lighting. Experiments should include classification accuracy, trajectory-tracking error, and transition-time continuity, as well as foot-placement error, actuator saturation, and safety events. Fault-injection experiments with misclassification, dropped frames and delayed information could determine how a controller recovers to conservative behavior and then switches back to normal assistance. Such directions are especially important in real-world deployment environments, where visual estimates may be delayed, and contact feedback may only show up after touchdown and may be of properties not expected. The principal limitation of the current evidence is the lack of directly comparable, whole-system evaluations across sensors, users, and terrain conditions; the methods discussed here should therefore not be treated as having demonstrated equivalent safety or performance. By evaluating perception quality together with decision timing, trajectory feasibility, and recovery behavior, future studies can establish clearer operating boundaries for terrain-adaptive exoskeleton assistance.

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