Recovery strategy identification throughout swing phase using kinematic data from the tripped leg

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***Abstract*—Falls are a large concern for individuals with lower limb amputations. Advanced powered prosthetic devices have the potential to quickly intervene after perturbations and help avoid a fall, but active balance recovery mechanisms have yet to be implemented. We investigated the feasibility of a real-time pattern recognition system for identification of trip recovery strategies. We tripped able-bodied subjects multiple times throughout swing phase and investigated the classification of walking, elevating and lowering strategies. Linear discriminant analysis was used throughout swing phase to classify kinematic data from the tripped leg. Window parameters that maximized classification accuracy were chosen from lengths of 50 to 200 ms and increments of 10 to 50 ms. We compared the performance of a single- and a two-stage (trip detection followed by strategy identification) classifier architecture. Optimal window length varied by classification stage, and window increment did not affect accuracy. The two-stage architecture performed significantly better overall, achieving a 92% median (range 88%-96%) accuracy across subjects compared to 88% (84%-96%) with the single-stage architecture. Most of the errors occurred immediately after the trip, with accuracies plateauing within 100 ms. Our results suggest that algorithms using data that can be measured from sensors embedded in robotic assistive devices could be used to trigger active balance restoring strategies following trips throughout swing phase.**

I. INTRODUCTION

Falls are a major concern for individuals who are older or have a disability due to the potential of causing an injury [1], thereby reducing their willingness to ambulate [2]. More than 60% of individuals with a transfemoral amputation recall falling at least once in the previous year [3]. Transfemoral amputees have difficulty recovering from trips [4], and the lack of support from the prosthesis during recovery often leads to falls [5]. Commercially available lower limb prostheses are functionally limited by their passive mechanical properties. One example of stumble-recovery mode–a response in which the knee provides high flexion resistance in response to a stumble–is still unable to help transfemoral amputees restore their balance following trips throughout all of swing phase [5].

A new generation of powered lower limb prostheses have the capability of providing net positive mechanical work [6, 7]. While these devices have been programmed for modes such as walking and stair climbing, they have yet to include a trip recovery mode. Able-bodied individuals recover from trips by either immediately lifting the tripped foot over the obstacle (i.e., an elevating strategy), or quickly lowering the tripped foot down to the ground to provide support (i.e., a lowering strategy) [8]. Transfemoral amputees attempt similar strategies [9], enabling powered devices to respond accordingly could improve recovery. However, selection between these two recovery strategies is not straightforward; while elevating strategies are used following trips in early swing and lowering strategies are used following trips in late swing, an overlap exists in mid-swing [10]. How strategies are chosen is not fully understood [11], and consequently cannot be well predicted.

Recovery strategies, however, have repeatable characteristics and it may be possible to identify the strategy once an individual begins to recover. Initial trip detection followed by strategy identification could enable accurate identification. Minimizing response time–or maximizing lead time to foot-strike–is critical to enable balance recovery. Differences between strategies can take up to 100 ms to occur, while foot-strike can be as early as 125 ms following a trip [10]. For a successful stumble recovery mode, trip detection, strategy identification, and enabled prosthesis response need to all occur within this time frame.

A similar time-sensitive classification problem that has been widely studied is fall detection. Multiple-stage, continuous-time approaches have been successfully used to distinguish falls from activities of daily living [12, 13]. Threshold-based algorithms monitor body segment velocities and accelerations and can accurately determine if a fall is occurring up to 700 ms before impact [13]. Similar algorithms based on thresholds of lower limb accelerations have been used to detect stumbles [14] and recovery strategies [15]. Although both studies reported near-perfect classification accuracies, the number of trips tested was small or restricted to single onset times in early and late swing phase. It is unclear how these algorithms would perform in response to trips throughout swing phase, specifically during mid-swing when both recovery strategies are used. A more advanced algorithm including pattern recognition classifiers has shown to be beneficial in identifying different ambulation modes [16, 17] and similarly may help to distinguish recovery strategies.

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In this study we investigated the feasibility of a real-time trip recovery strategy classification system. We studied the effect of two different classifier architectures and a range of analysis window parameters on the classification accuracy of walking, elevating and lowering recovery strategy classes. We hypothesized that a two-stage architecture would result in higher accuracies than a single-stage architecture. We also hypothesized lower accuracies in the tripping trials when compared to the walking trials due to large errors immediately following the trip.

II. Methods

A. Data Collection

Eight able-bodied subjects (24 ± 2 years old, 1.70 ± 0.07 m, 64.3 ± 9.5 kg) were tripped using a custom-built device [11] while walking on a treadmill at 1.4 m/s. A tether attached to either foot arrested forward movement of the foot for 150 ms during swing phase. Trips were induced on the right and left sides at 6 different points in swing phase (10% to 60% of swing phase in 10% increments). Each side-onset combination was repeated six times. To avoid anticipation, trips were applied in random order and separated by at least one minute. Five baseline walking trials were collected throughout the tripping trials.

Motion capture data from the pelvis and lower limbs were acquired at 100 Hz. Forces were obtained from load cells (LC703-50, Omegadyne, Sunbury, OH) attached along the tripping tethers and from force plates embedded in the treadmill (ADAL 3D-F/COP/Mz, Medical Developpement, Andrézieux-Bouthéon, France). Analog data were sampled at 1 kHz. Data were collected synchronously in Cortex (Motion Analysis, Santa Rosa, CA).

Motion data were exported to Visual3D (C-Motion, Germantown, MD) to obtain joint angles. All data were then exported to Matlab (The Mathworks, Natick, MA). Ground reaction forces were used to identify foot-strike and toe-off. Trip tether loads were used to indicate trip timing. An automated algorithm was used to identify recovery strategies based on the difference between post-trip foot trajectories and baseline walking [11]. We only analyzed trip trials that resulted in elevating (25 ± 12 trials across 6 subjects) or lowering (32 ± 17 trials across 8 subjects) strategies.

B. Classifiers

Two separate, subject-specific, linear discriminant analysis classifier architectures were investigated (Fig. 1a). A single-stage architecture was trained to recognize the difference between 1) walking, 2) tripping recovery with an elevating strategy, and 3) tripping recovery with a lowering strategy. A two-stage architecture was trained to first recognize the difference between walking and trips (i.e., trip detection) and then, if a trip was detected, recognize the difference between the elevating and lowering recovery strategies (i.e., strategy identification).

Sliding analysis windows were used to continuously classify the data from toe-off to foot-strike. The effect of window parameters on classification was investigated. Window lengths of 50, 100, 150 and 200 ms and window increments of 10, 20, 30, 40 and 50 ms were tested.

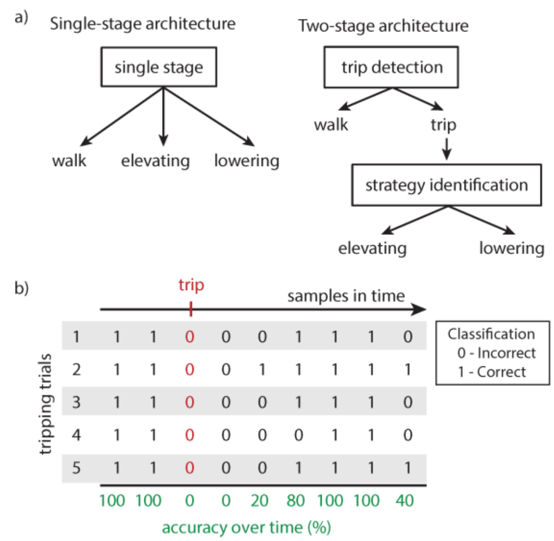

Figure 1. Classifier architectures and accuracy calculation method. a) A single- and a two-stage architecture were tested. b) Accuracies for a class over time were the average at each window increment across trials.

In order to investigate the feasibility of a system contained within a transfemoral prosthetic device, only data from the tripped leg that could be measured with embedded sensors were used. Kinematic data consisted of the following sagittal plane variables: knee and ankle angle and acceleration, and foot acceleration magnitude. Because of the short window lengths and low frequency content of these variables, time-domain features extracted were minimum, maximum, mean and standard deviation [17].

C. Analysis

A single swing phase was extracted from each trial. For walking trials, we used the second swing phase of the left leg. For elevating and lowering strategy trials, we used the swing that contained the trip. Elevating and lowering strategy trials were labeled as walking until the trip, after which they were labeled as a trip or the respective recovery strategy depending on the classification stage. Two out of the eight subjects recovered from trips only using lowering strategies, so their data were not included in the strategy identification classifier. Due to the limited number of trials per subject, classifiers were evaluated using leave-one-out cross-validation. Class accuracies were calculated as the average across all trials within each class. Accuracies for each subject were the average accuracies across classes.

The effect of different window parameters on classification accuracy was analyzed for both architecture types and for each class. First, we determined the effect of window length for each window increment. For each classifier stage, the length that resulted in statistically higher accuracy for the largest number of increments was chosen. For each optimal length, we compared the effect of window increments and chose the increment that resulted in highest accuracy. Once both window parameters were determined, classifier architectures were compared.

Classification accuracy over time was calculated as the average accuracy for each time point across trials (Fig. 1b). Walking trials were lined up at toe-off, and elevating and lowering trials were lined up at trip time. Time was limited to the length of the shortest trial across all subjects, to constrain the classifier to the shortest response times.

Statistical analyses of classification accuracy included nonparametric Friedman ANOVAs and post-hoc tests with Bonferroni corrections. Classifier architectures were compared with sign-tests. Significance was at the 0.05 level.

III. Results

A. Window Length

Optimal window length depended on both classification stage and data class (Fig. 2). In the single-stage classifier, window length affected walking class accuracy for all window increments, while elevating and lowering classes were affected in few cases. Window length affected the accuracy of elevating strategies in trip detection, and both elevating and lowering strategies in strategy identification.

Optimal window lengths were consistent for each classifier, as indicated by post-hoc comparisons. For the single-stage and trip detection classifiers, window lengths of 50 and 100 ms achieved significantly higher accuracies over a range of window increments when compared to 150 or 200 ms ($p<.05$) (Fig. 2). For the strategy identification classifier, window lengths of 150 and 200 ms outperformed 50 ms ($p<.05$). There were no significant differences within the shorter (i.e., 50 and 100 ms) and longer (i.e., 150 and 200 ms) window lengths. Thus, we chose the shortest length of each group to reduce the data processing requirements. For the single-stage and trip detection classifiers we used a 50 ms window length and for the strategy identification stage we used a 150 ms window length.

B. Window Increment

There were no significant effects of window increment for the optimal window lengths chosen above. Thus, we used the shortest increment (i.e., 10 ms) as this outputs decisions more often and potentially allows more time for recovery.

When comparing the overall classification (Fig. 3), the two-stage architecture was significantly better than the single-stage classifier ($p<.05$). All trip trials were correctly identified in at least 1 analysis window in both architectures.

C. Errors Over Time

Most errors occurred during tripping trials (Fig. 4). Trip detection errors were concentrated immediately after the trip; 60 ms after the trip, average error rates were less than 10%. Strategy identification was less accurate for elevating compared to lowering strategies during most of recovery. Overall accuracies for both classifier architectures plateaued within 100 ms after the trip.

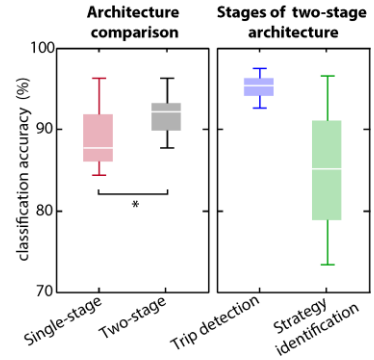

Figure 3. Classification accuracy across subjects for the single- and two-stage architectures (left) and trip detection and strategy identification stages (right). Asterisk indicates significant differences (p<.05).

IV. Discussion

This study was the first to attempt identification of recovery strategies in response to multiple (more than 20) trips throughout swing phase. By separating classification into two stages, we were able to statistically improve the overall accuracy (92% median accuracy) compared to using only one stage (88% accuracy). The two-stage architecture took advantage of the similarity between the tripping classes to distinguish them from walking data, as suggested by the improved classification of walking trials when compared to the single-stage architecture (Fig. 4). Strategy identification was also improved, resulting in slightly higher accuracies during recovery. The optimal window lengths associated with each classification stage were likely related to the ability of the short windows to quickly capture the changes due to the trip, while longer windows better represented the slower kinematic characteristics of the strategies. Our results show that continuous pattern recognition classifiers can be used to accurately and quickly identify able-bodied subjects' response to trips.

While trip detection accuracies were less than 100%, both architectures correctly detected the occurrence of all trips. This is because overall accuracies reflect delays in detection and errors in walking trials. As expected, classifier errors were concentrated immediately after each trip. Errors in trip detection increased drastically at trip time, but reduced to less than 10% error 60 ms after the trip. It is possible that kinematic patterns at the end of swing are similar across classes, which could have prevented further increase in accuracy. Implementing a voting scheme, or incorporating time-history, could increase post-trip accuracy, although at the cost of increasing the delay. For example, if a trip were detected at multiple increments, the trip class could be held until foot-strike. This could also improve walking

Figure 2. Effect of window length on classification accuracy for walking (*left*), elevating (*center*) and lowering (*right*) classes. Window lengths were compared for each window increment. Gray shading indicates a significant effect of window length. Significant post-hoc comparisons are indicated by black squares, with the better length(s) in the vertical direction, and the worse length(s) in the horizontal direction.

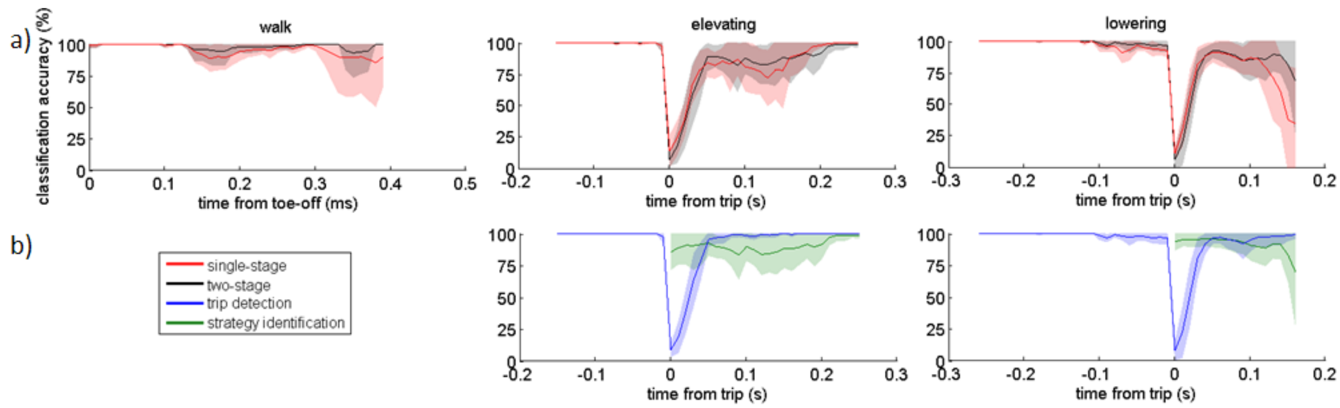

Figure 4. Classification accuracies over time for each class in the a) single- and two-stage architectures, and b) trip detection and strategy identification classifiers. Lines are averages across subjects with shaded standard deviations.

accuracy, as repeated misclassifications should be less likely to occur. Reducing false positives (i.e., detecting a trip when no trip has occurred) is very important for patient safety.

Our data set included trips throughout swing phase, while previous trip detection [14] and strategy identification [15] studies focused only on trips in early or late swing. In these studies all trip trials were also correctly detected, with less than 0.01% walking misclassification. Trips in early and late swing were detected at least 100 ms ahead of a critical body inclination angle [14], which is similar to our minimum lead time before foot strike. This might not be enough time to generate large corrective motions, but may allow the device to prepare for weight bearing and avoid falls due to lack of body support [5]. Trip detection and strategy identification were previously achieved within 50 ms of the trip [15], which is similar to our trip detection delay and within the reaction delay in human subjects [10]. Our accuracies, however, are lower; in particular, the strategy identification stage should be improved. Future studies could explore these proposed algorithms on trips with varying onsets.

This study had some limitations. We only tested on data from able-bodied individuals; the same approach is easily applicable to amputee data. Additionally, it is possible that only a subset of the kinematic channels used are providing the most important information for classification, and the number of sensors required could be reduced. We tested and trained the classifiers on data from the same subject, but an across-subject classifier would be beneficial in practice.

V. Conclusion

As assistive and prosthetic robotic devices are further developed, they must accommodate more situations that are common in daily life such as perturbations during gait. Our results suggest that trip detection and strategy identification are feasible with a continuous pattern recognition-based classifier. Further improvements to the classification system and generalization across subjects should be explored.

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