

Automating Human Motor Performance Ability Testing: The Case of Backward Step Detection

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Abstract—Coordination under precision demands is an important aspect of human motor performance ability. It is usually evaluated through a carefully selected set of physical exercises, which follow the same scheme: An examiner presents candidates with a task to perform, monitors their correct task execution, and manually tracks the score achieved by each candidate. However, the latter two steps impose a significant cognitive load on the examiner. Even short losses of attention while carrying out the (often monotonous) test procedures may lead to erroneous results being reported. An automated solution of determining test results would not only reduce the required degree of examiner attentiveness, but potentially even accelerate testing thereby. However, such a system has not yet been proposed to the best of our knowledge. We fill this gap by presenting an approach towards the automation of the “balancing backwards” motor performance ability test in this paper. Its objective is to quantify locomotion ability by counting the number of backward steps a test subject can take when balancing on a narrow aluminum beam. We analyze the design space for backward step counting and derive a sensor configuration tailored to the autonomous detection of the number of steps taken, based on gyroscope data and laser light barriers. The system design is followed by an evaluation of its achievable accuracy levels in real-world tests, which confirm its practical viability.

I. INTRODUCTION

The motor performance ability (MPA) is tightly linked to the fitness and wellbeing of people of all ages. Building up and maintaining MPA is easiest achieved through regular physical exercise. However, studies (such as the one conducted in [24]) unambiguously demonstrate that both volume and intensity of physical activity among children have experienced a gradual decline in the last decades. Moreover, an inverse relation between MPA and body fatness of children has been determined in [15]. Thus, an early intervention to gradually declining movement abilities is crucial. A viable way to accomplish this is by adapting physical education classes in primary schools to the changing needs of children. Moreover, knowledge of children’s movement ability deficiencies allows local sports clubs to adapt their course offers and may even influence (political) decisions on the extent of physical activities in schooling.

In order to implement such measures, however, the status quo needs to be determined first. Methods to capture and assess people’s MPA have been proposed in [7, 8, 16, 37, 41]. These tests, commonly composed of a set of tasks to execute,

provide proficiency indicators in key areas such as endurance, strength, speed, coordination, and agility [8]. In the majority of tests, a point scoring system is being used to rate the candidate’s performance in each task, with their sum representing an overall indicator of their MPA. A test instructor oversees the participants during testing and tracks the results for each task, usually through entering them into a paper-based form. Despite the ubiquitous presence of IT systems, however, a trend towards test automation cannot be currently observed. Thus, the test instructor does not only have to monitor tasks for their correct execution, but must also count scored points properly and possibly provide assistance to test candidates.

We strive to overcome this limitation by providing a simple, yet reliable solution for MPA test automation based on networked embedded systems. Our system autonomously computes scores for a test task, allowing the instructor to exclusively focus on monitoring the proper execution of the task. In particular, we have chosen the “balancing backwards” test task from a set of German MPA tasks called *dmt 6–18* [8]. The objective of the selected task is to place as many backward steps as possible without touching the ground while balancing on a narrow aluminum beam. While the test task may sound straightforward, its automation requires several parameters to be monitored simultaneously. Firstly, the step counting process must only start when both feet have been placed on the aluminum beam. Secondly, the step counting process must be stopped when either the end of the beam has been reached, or the test candidate’s foot touches the floor instead of the beam. At last, the number of steps on the beam must be determined using a suitable sensing modality, converted to the test score, and stored in a database for further analysis.

All of these items are covered in the key contributions of this paper, which we summarize as follows:

- We summarize the rationale behind MPA testing and provide details on the backward balancing test used in the evaluation of our contribution.
- We derive design goals and a concept for the automated assessment of the backward balancing test and present important implementation details.
- We evaluate the accuracy of our approach through conducting experiments with four test candidates and quantify its step counting accuracy.

We introduce the concept behind human motor performance ability testing in Sec. II, where we also provide more detail on the “balancing backwards” task. Subsequently, we discuss related scientific work to capture human motion using embedded sensors in Sec. III. More details on our approach to automate the chosen MPA task and the actual system implementation are provided in Sec. IV. We evaluate the accuracy of our testing setup through practical experiments in Sec. V and conclude this paper in Sec. VI.

II. HUMAN MOTOR PERFORMANCE ABILITY TESTING

Physical fitness has a provable impact on human health. Building up and maintaining fitness is a widely followed goal, as manifested by steadily increasing health club membership numbers [18]. To tailor training sessions to the needs of the individual, it is pertinent to quantify a person’s motor skills and abilities through testing [12, 26]. Knowledge about weaknesses and strengths of a person’s motor performance ability can be used in manifold ways. Firstly, tracking of performance histories allows for the optimization of exercise schedules, such as through functional training [11]. Secondly, health-related questions can be answered more comprehensively when test results are available. At last, testing allows for the identification of subpopulations and talents. Such information can be used, e.g., to test whether a respondent relies more on the vestibular system or the visual system when performing a balancing task [14].

A. The “balancing backwards” Task

We base our investigation on the Deutscher Motorik-Test (*dmt 6–18*) test suite [8], a representative example of a set of motor performance ability tasks. Our choice of the *dmt 6–18* was furthermore motivated by the availability of a hardware kit, which allowed us to also consider practicality aspects. “Balancing backwards” is one of the tasks in the *dmt 6–18* to assess coordination under precision demands. Its objective is to determine the dynamic whole-body balance for students in the age range between 6 and 18 years by measuring the ability to coordinate limbs precisely through locomotion movements.

The task setup is schematically shown in Fig. 1. Test subjects begin the task by placing both of their feet on a start panel of 40 cm by 40 cm in size. Subsequently, subjects need to balance backwards along a beam of 3 m length. The test instructor counts the number of steps the test subject takes on the beam before touching the floor or reaching the end of the beam. The number of steps on the beam, counted from the moment the second foot leaves the start panel, is used as

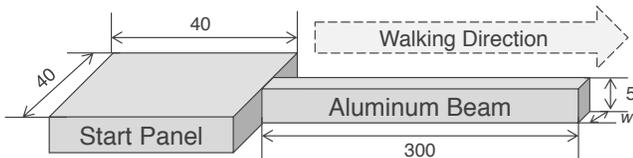


Fig. 1. Schematic test setup of the “balancing backwards” test. Dimensions in centimeters (not true to scale). Three aluminum beams of different widths ($w=3$ cm, 4.5 cm, 6 cm) are part of the test; they can easily be swapped.



Fig. 2. Sample user balancing backwards on the beam of 3 cm width.

the test score. The very first step (one foot on the beam, the other one still on the start panel) is ignored. When more than 8 steps have been taken on the beam or the end of the beam is reached, 8 points are recorded.

The subjects have to perform six trials in total, two for each of the different beam widths $w=3$ cm, 4.5 cm, and 6 cm. The total score is computed as the cumulative number of steps taken in all attempts to master each of the three beam widths twice, consequently a maximum number of 48 points can be scored in the six permitted trials.

B. Observations from Preliminary Experiments

Prior to designing our system for test automation, we have set up the “balancing backwards” experiment in a gymnasium. Students with different levels of fitness were asked to execute the task according to the instructions, and their performances were recorded on video. Our objective of these preliminary experiments was to gain insights on boundary conditions relevant for the automation of the test. Three video frames of one user balancing backwards on the beam of 3 cm width are shown in Fig. 2. Through analyzing the video footage from the preliminary experiments, the following insights were gained:

- 1) When balancing backwards, the entire foot is lifted at once for each step taken. This is in contrast to forward walking, where the toe and heel are lifted in sequence.
- 2) Walking on the beam differs from flat surfaces in that there is almost no vertical hip motion.
- 3) A slight hip rotation can be detected when balancing (forward or backward). However, its amplitude is relative to the length of the steps taken. As short strides are prevalent when balancing backwards, the user’s hip only rotates imperceptibly.
- 4) Balancing is executed much more slowly (between 0.2 and 0.7 steps per second, at an average of 0.4 steps taken) than walking at regular pace.
- 5) There is no continuous movement in the direction of the beam, because test subjects frequently take breaks to (re-)gain their balance. Thus, no periodic patterns could be visually detected in balancing tasks.
- 6) Subjects are deliberately put into a *test situation*; in terms of prior training, only a single test run on each beam width is allowed before the experiment. Thus, there is little to no calibration data available for the initialization of the system.

- 7) The beam is only 3 m long. In comparison to the average distance a human being walks per day, this is extremely short. Only very few steps (at most 8) on the beam are counted for the experiment, thus a small error (one mis-counted step) already introduces a significant measurement error.

C. Resulting Design Considerations

Considering the observations listed above, our system must be capable of accurately counting the number of backwards steps taken even under difficult conditions. The system must autonomously adapt to the candidate performing the test, given that it will not have any long-term training data available. As different participants will use it in quick succession, any devices to be worn must work reliably even when positioned inaccurately. Moreover, body-worn sensing devices must be designed in a way that caters for their quick removal and re-application on another subject. The measurement system may be used in a multi-user environment, such as a gymnasium, which results in a high chance of other sports activities taking place in parallel. It thus has to be resilient to such external influences. At last, wireless operation should be preferred wherever possible to avoid the risk of injury when subjects accidentally get entangled in data or power cables.

III. RELATED WORK

The field of human gait tracking and analysis has received strong scientific attention in the past. Even though the automation of MPA tests, in particular “balancing backwards,” has rarely been addressed specifically, the two research areas share many commonalities. A key design decision to make is whether the step counting system can be intrusive (i.e., rely on body-worn sensor devices) or not. More sophisticated sensor readings (such as the hip rotation) can be acquired when sensors are worn on or close to the body. At the same time, ensuring a correct sensor fit is inevitable to avoid erroneous measurements. We summarize works from both fields which may serve as foundations for our research goal as follows.

Step counting is an important prerequisite for indoor navigation due to the unavailability of GPS signals in buildings. Consequently, several approaches towards step counting have been presented in related work, e.g., [2, 4, 9, 23, 36, 40]. The number of steps is often estimated using acceleration data. However, unless a system is highly trained to its user, aspects like an individual’s stride length or the presence of noise in sensor data lead to inaccuracies. For example, the work by Alzantot and Youssef presented in [2] has only focused on forward motion and assumes a steady step frequency. This contradicts our observations of users taking steps very slowly and at an irregular rate and when balancing backwards (cf. Sec. II-B). This insight is also confirmed in [3, 25], where stride lengths have been shown to strongly vary when the step frequency is low. The applicability of step counting algorithms based on acceleration data thus appears to be limited.

In contrast to purely acceleration-based step counting approaches, angular rate sensors have been utilized in works like

[20, 21]. Gyroscopes have been shown to particularly improve the detection of steps taken slowly [6]. In the work by Mondal et al. [30], gyroscope data have even been demonstrated to be suitable for differentiating (even identifying) people based on their gait. Despite their applicability to accurately capture slow step motions, however, the use of gyroscopes for backward step counting has not been analyzed in literature so far.

Two works relying on intrusive sensor setups have specifically focused on the detection of walking backwards. Lijffijt et al. have recorded traces for backwards walking on a line drawn on the ground (i.e., not raised like the aluminum beams in our case) using acceleration data collected in different positions on the body [27]. Likewise, Ito has considered the combination of acceleration measurements with shoe inlays to track ground contacts [19]. Both works have highlighted the need for a precise positioning of the accelerometer in relation to the candidates’ bodies. This limits their applicability to MPA tests when a large numbers of participants are present, as the careful sensor fixation can be expected to be a time-consuming step.

In contrast to the intrusive approaches discussed above, it is also possible to instrument the environment in order to localize persons and count the steps they take. To this end, Zeng et al. have demonstrated a way to recognize people simply based on how they impact on wireless LAN transmissions [39]. In work presented by Adib et al. in [1], an even better recognition rate is demonstrated, however at the cost of highly specialized antenna designs. Passive localization has also attracted research interest in the wireless sensor networks community, e.g., to detect people’s movements within buildings, such as demonstrated in [17, 22], yet they are not sufficiently fine-grained to confirm individual steps taken on the beam.

Another non-intrusive approach to count backward steps is the addition of pressure-sensitive surfaces on the aluminum beam as well as beside it. This approach has been successfully applied in adjacent scenarios, e.g., to detect a person’s sleeping position based on a self-constructed pressure-sensitive bed cover in [28, 29]. Other works have looked into user activity recognition based on pressure data (e.g., [10, 35]), however these were primarily targeted at discriminating between activities, with no monitoring of fine-grained details. We have researched on the availability of a sufficiently large pressure-sensitive mat that covers the complete area around the aluminum beam, yet not found any commercially available product in the required dimensions. Alternatively, pressure-sensitive surfaces can be inserted into a shoe sole (such as proposed in [5, 34, 38]). While this approach is intrusive and possibly requires more time when switching between test subjects (and even an adaptation to different shoe sizes), it allows for step counting in principle. Differentiating between steps taken on and beside the beam is, however, not possible.

The visual analysis of test subjects is the last prevalent approach identified in related work. Video analysis to classify general user motions is performed in [13]. A system design to count how many forward steps a user has taken is presented in [30]. However, an important prerequisite for all camera-based solutions is the need to robustly mount cameras in fixed

positions. The conditions prevailing in the test environment (e.g., the absence of mounting points to fix cameras in exact positions) do not allow for approaches with high accuracy requirements to the sensor placement. Moreover, being recorded on video introduces data privacy issues, particularly as the target group of *dmt 6–18* is constituted solely of minors.

IV. SYSTEM DESIGN AND IMPLEMENTATION

In our survey of related work, we have identified the use of gyroscope data as a promising candidate for accurate step counting, even when the sensor is not accurately positioned. On these grounds, we have decided to explore the potential of using gyroscopes to count the number of steps taken in the “balancing backwards” test. In order to use gyroscopes for step counting, the sensors need to be placed on the human body in positions where rotational motion occurs with every step taken. An intrusive sensor setup is thus pertinent, with step counting sensors preferably affixed to subjects’ lower limbs. This choice makes the use of wireless sensors inevitable, as wired connections would increase a high risk of candidates becoming entangled in the cables while performing the balancing task.

While we have decided to detect and count steps with the help of gyroscope data, supplementary information about the beginning and end of each trial is required to report the correct test score. As outlined in Sec. II-A, scoring must only commence when both feet have left the start panel. Any steps taken before that (e.g., walking to the start panel) must not count towards the test score, even though they may also be detected by the gyroscope.

Three conditions are defined to terminate a test: (1) Completing eight steps on the beam, (2) balancing backwards past the end of the beam, or (3) stepping beside the beam. While the first criterion can be directly derived from the step counter implemented using gyroscope data, our preliminary experiments have not shown dissimilar motion patterns between steps taken on the beam and beside it. For a reliable detection of the necessary conditions to start/end a task, supplementary sensors are thus required. We use light barriers to detect whether the start panel is occupied and to check if a subject has stepped beside the aluminum beam. Optionally, a light barrier can be added to the end of the beam. We have not included it in

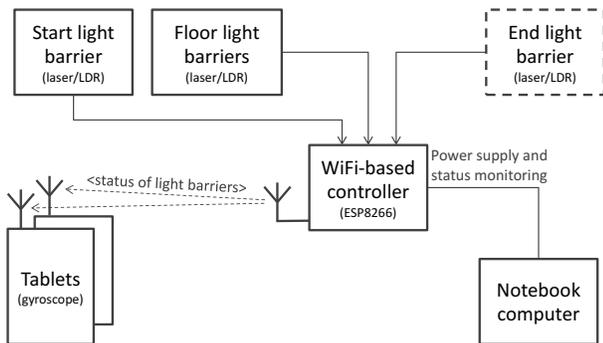


Fig. 3. Overview of the system’s main components and their interconnections.



Fig. 4. Axis orientations of the gyroscope sensors mounted on a test subject’s lower legs. Note the inverted orientations of x-axis and z-axis between the devices due to their symmetric mounting.

our design because all subjects completed their trials before reaching the end of the aluminum beam in preliminary tests.

An overview of the interconnections of these key components is shown in Fig. 3. The light barriers depicted on the top of the diagram cater to the detection whether an experiment’s start/end conditions are met, and thus allows us to differentiate between separate balancing iterations. Tablet computers are used to collect gyroscope data and determine the number of steps taken. At last, a controller device is employed to continuously interpret the light barrier outputs and send these to the tablet computers via a WiFi connection in order to start/stop their step counting. We discuss design considerations and implementation choices in more detail as follows.

A. Using Gyroscopes for Step Counting

Gyroscopes measure angular velocity, thus it is necessary to mount them in a position where rotations occur with each step. Based on insights from related works [9, 36], the lower leg is the preferred location because of its motion during each step. Consequently, we have decided to place the sensors in this position, as depicted in Fig. 4. As can be observed from the picture, 7-inch tablets (Google Nexus 7¹) have been used in our prototypical setup. Without loss of generality, however, any other device with a gyroscope sensor and processing capabilities could be used instead, e.g., smartphones or sensor nodes like the Shimmer mote [33].

Based on responses to our preliminary trial runs (cf. Sec. II-B), sensing devices on candidates’ lower legs are not perceived as obstacles as long as they are not too heavy and mounted symmetrically (i.e., on both legs). The gyroscope has intentionally been placed a small distance away from the candidates’ feet towards the fibula (lower leg) to avoid undesired tilting and rotation introduced by the ankle joint. The devices were attached using rubber bands in our prototype; our analysis of the step counting accuracy presented in Sec. IV-B confirms the sufficiency of this imprecise placement. In order to count the number of steps taken with each foot, tablet computers are mounted in a mirrored fashion on the outsides of a candidate’s legs. As visible in Fig. 4, the orientations

¹Hardware specifications at https://www.asus.com/us/Tablets/Nexus_7_2013/specifications/; the devices were running Android version 6.0 (API 2.3).

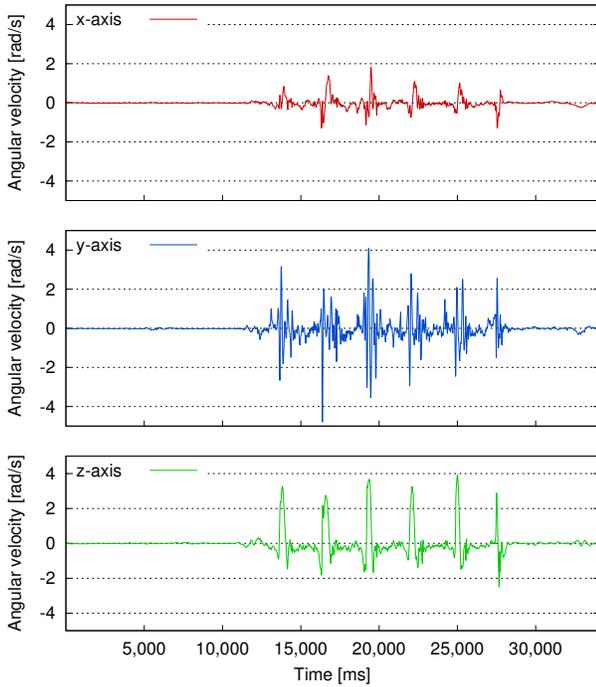


Fig. 5. Gyroscope recording of eleven backwards steps; trace for one leg shown in the diagram, thus only every second step leads to an excitation.

of their x-axis and z-axis are inverted due to the symmetric mounting. Simple value inversions along these axes for one leg suffice to allow the same data processing algorithms to be run for both legs.

An excerpt of gyroscope data recorded from backwards balancing on the 4.5 cm wide aluminum beam is shown in Fig. 5. Keeping in mind that only data from the left leg are visualized in the figure, the presence of six excitations indicates that a total number of eleven or twelve steps have been taken. Through the visual analysis of a video recording taken simultaneously, we could confirm that ten steps were taken on the beam and one on the ground after the experiment.

Knowledge of the presence of six excitations allows for the visual detection of spikes for each step taken on all three axes from Fig. 5. Spikes of the rotations around the x-axis and y-axis are, however, pronounced much less clearly than the rotations around the z-axis. Moreover, their data is surrounded by more irregularities. In contrast, on the z-axis of the trace periods of small angular velocity values are always followed by a big excitation. This can be explained by the fact that the z-axis captures rotations around the knee joint, which are an inherent element of the human gait cycle [32]. Thus, we will be exploiting the rotation around the z-axis for counting the number of steps in software, as detailed in the next section.

B. Extracting Steps from Gyroscope Data

In order to extract the number of backwards steps from collected gyroscope data, we have developed an Android mobile application. Its key functionalities are to retrieve samples from the gyroscope and apply processing to determine the number of steps taken therein. Moreover, it has been designed to react

to signals of the light barriers received via the WiFi controller, as will be detailed in Sec. IV-C. Gyroscope data are sampled using a sampling period of 20 ms (`SENSOR_DELAY_GAME`). At typical step frequencies (cf. Sec. II-B) well below the corresponding sampling rate of 50 Hz, we expect no information loss to occur due to undersampling. The recorded traces are being buffered for their a posteriori analysis, with the beginning and end of each candidate’s attempt determined through the signals received from laser light barriers.

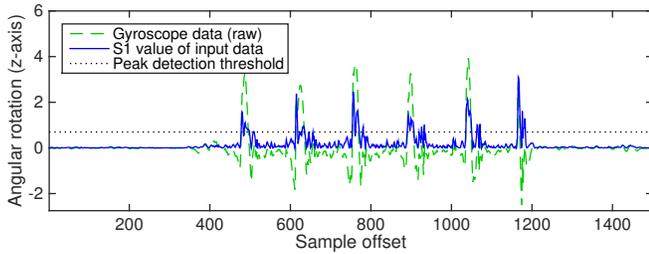
For our development of a routine to extract the number of steps from time-series gyroscope data, we have run two preliminary data collection experiments with volunteers. In the first set of trials, we acquired gyroscope data from people balancing backwards on the actual aluminum beams. In the second set of test runs, supplementary test runs have been conducted and recorded when walking backwards on an even surface, following a 15 m long line marked on the floor. Both experiments were conducted in a controlled environment without external influences (i.e., other sports activities taking place simultaneously) to reduce irregularities and noise. They served as training samples in the design and development of the actual step detection algorithm, which we detail as follows.

We base the design of our algorithm to extract the number of backward steps from the collected gyroscope data on the observations made in Fig. 5, as well as other traces collected during our preliminary experiments. The analysis of traces from the latter source of data has, e.g., indicated that a simple thresholding-based approach (such as recommended in [21]) cannot be applied in the given context. The reason is that greatly different angular velocity amplitudes could be observed across different subjects tested. However, the characteristic and recurrent peaks of z-axis rotation data for each step taken has unequivocally been present in all collected data. It can thus be seen as a viable indicator for the occurrence of steps.

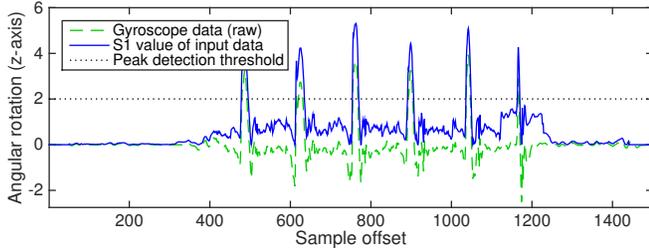
We have consequently derived a solution based on work by Palshikar [31] and implemented it for mobile sensing devices. More specifically, we have used the significance function $S_1(k, i, x_i, T)$ to determine the probability if a value x_i is a local peak in the vicinity of its k left and k right neighboring values within the time series T . The function S_1 is applied to each value x_i in T as long as it has at least k left and k right neighbors, in analogy to a sliding window algorithm. It is defined in Eq. (1).

$$S_1(k, i, x_i, T) = \frac{\max\{x_i - x_{i-1}, \dots, x_i - x_{i-k}\}}{2} + \frac{\max\{x_i - x_{i+1}, \dots, x_i - x_{i+k}\}}{2} \quad (1)$$

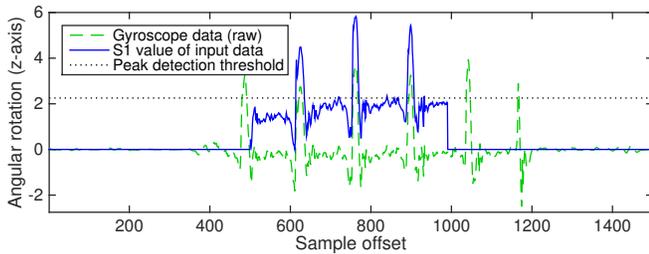
Our step counting algorithm takes the gyroscope time series T as the input and computes its significance function S_1 . The resulting data can be seen as an indicator of the likeliness of a value peak to be present at a given location x_i . Subsequently, mean m and standard deviation sd across all values returned by S_1 are computed, and a threshold of $m + 1.5 \cdot sd$ is defined, as per the recommendation in [31]. The computed threshold is being used to discern between step candidate peaks (with S_1



(a) S_1 significance value for $k=5$.



(b) S_1 significance value for $k=50$.

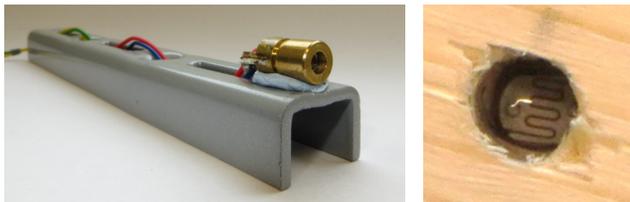


(c) S_1 significance value for $k=500$.

Fig. 6. Z-axis gyroscope data and the corresponding S_1 values.

values exceeding the threshold) and peaks that do not indicate a step; all positions in the latter category are discarded from the list of peaks relevant for step detection. The temporal distances of remaining peaks are analyzed and physically impossible constellations (i.e., two steps taken with less than half-second gap in between) are eliminated. At last, only the strongest peak in each time window of length $2k+1$ is retained and considered as the indicator of a backward step.

A visual comparison of z-axis raw gyroscope data and the corresponding S_1 values for three different values of k is shown in Fig. 6. Two observations can be made from the figures. Firstly, they confirm that detecting and counting zero crossings (as proposed in [21]) is not a viable method to detect backward step due to the irregular fluctuations of raw measurements around the zero crossing. Secondly, peaks occur repeatedly in the data for each step taken. Their amplification



(a) Laser diode on mounting bracket. (b) LDR in wooden block.
Fig. 7. Laser diode and LDRs in their mounted positions.

TABLE I
POSSIBLE LIGHT BARRIER VALUE COMBINATIONS.

Start platform light barrier	Light barriers beside aluminum beam	
	uninterrupted	interrupted
interrupted	Ready to start experiment; wait for subject to leave platform	Transition phase in-between experiments (two subjects in the area)
uninterrupted	Experiment in progress; record gyroscope data	Subject stepped on the floor; stop data recording

through the application of the S_1 function makes them even more pronounced and simplifies their detection. Recalling the sampling frequency as 50 Hz and a backwards step frequency lower than 1 Hz, we have used $k=100$ samples as the default setting for our peak detection algorithm, i.e., we use a time window of two seconds before and after a step.

C. Triggering Data Recording through Photoelectric Barriers

Having outlined how steps are extracted from gyroscope readings is only one of the two key prerequisites to automate the backwards balancing test. The second requirement is to determine the beginning and end of each test run, in order to autonomously start/stop the recording of gyroscope data on the tablet devices. We have decided on using light barriers to this end. Based on empirically determined values for the maximum sideways stepping length of around 40 cm on either side of the beam, we have interspersed this region with laser diodes pointed at light-dependent resistors (LDRs) lined up beside the starting platform. The horizontal distance between laser diodes has been selected as 7.5 cm in order to even detect children's feet. To determine the beginning of an experiment, another light barrier has been mounted across the starting platform to detect any objects placed on it. All LDRs are embedded into blocks of wood to reduce the impact of stray light on the detection rate, as visible in Fig. 7.

A wireless controller device has been prototypically developed on the basis of an ESP8266 device to act as a wireless access point, to which the mobile tablet devices connect. It samples each attached LDR at a frequency of 10 Hz in order to determine whether a light beam is interrupted. This information is evaluated according to Table I and resulting status messages are broadcast to the connected tablet computers. The two tablet computers react according to the messages and either begin or stop sampling the data as well as displaying the counted steps after each trial for easy verifiability.



Fig. 8. Test setup with activated light barriers. Laser diodes are placed on the left; corresponding LDRs for detecting steps beside the beam located on the right. The notebook PC supplies power to the controller and laser diodes.

TABLE II
ACTUAL AND DETECTED NUMBER OF STEPS ON ALUMINUM BEAMS OF STATED WIDTHS WHEN VARYING THE WINDOW SIZE PARAMETER k .

	By participant ID				By width of the aluminum beam		
	A	B	C	D	6 cm	4.5 cm	3 cm
Total number of steps placed on the beam (ground truth)	56	29	45	49	84	77	18
Number of steps detected when setting $k=100$	49	20	39	31	68	55	16
Number of steps detected when setting $k=50$	60	36	46	42	92	70	22
Number of steps detected when manually selecting $k=50$ or $k=100$	52	25	43	42	76	68	18

V. EVALUATION

After presenting our system design, we evaluate it under realistic conditions next. The evaluation setup follows the description in Sec. IV. Two Nexus 7 Android tablets were used to collect gyroscope data. Five photoelectric barriers have been placed on each side of the beam to detect steps on the floor, and a light barrier has been mounted on the start panel. A picture of the experimental setup is shown in Fig. 8. During each trial, gyroscope data of both tablet computers were collected (while the light barriers triggered the data recording) and stored into an in-memory data structure for step detection. A backup copy was moreover stored into a file for offline analysis. Once the light barriers had indicated the end of a trial, each tablet executed the step counting algorithm presented in Sec. IV-B. Tablets were mounted on the participants' lower legs using rubber bands, as shown in Fig. 4. The system has been set up in a gymnasium with no other sports activities taking place simultaneously.

A. Practical Evaluation under Test Conditions

To evaluate the efficacy of our proposed solution, we have invited four participants to take part in the "balancing backwards" test. Experiments have been performed according to the test rules, i.e., no more than six trials were allowed (two for each beam width). In total, 24 repetitions were conducted and both gyroscope and light barrier data as well as a video recording (to determine the ground truth) have been captured. The step detection window size of the S_1 significance measure (cf. Sec. IV-B) has been set to $k=100$ initially. Test results are tabulated in Table II, categorized by participant ID and by the width of the aluminum beam. As a part of the experiments, we have asked the participants for their height, shoe size, age, gender, and how often they exercise per week on average. These personal data of our test subjects are summarized in Table III to cater for a better understanding of the results.

As an overall result, it can be observed that the system is capable of capturing up to 100% of the steps are detected (on the 3 cm beam, where steps are usually taken more slowly). However, a non-perfect step detection rate has been identified

TABLE III
DETAILS OF THE FOUR TEST SUBJECTS.

	Participant ID			
	A	B	C	D
Height (in cm)	179	174	182	164
Shoe size (EU)	43	44	44	39
Age (years)	24	29	28	28
Gender	male	male	male	female
Weekly sports activities	3	5	1	3

when using $k=100$, with the fraction of correctly detected steps ranging between 63.3% (D) and 87.5% (A). The detection rate is particularly poor for participant D, who was completing the lengths of the beams at brisk pace. This can be attributed to the peak detection window value (cf. Sec. IV-B) of $k=100$, which has been found to be too large to allow for detecting fast steps. An off-line repetition of the analysis was thus conducted for the data with $k=50$, but false positives (i.e., too many counted steps) were observed in many cases. When both values of k are analyzed manually for each collected trace, and the more accurate of the two results is taken, the results shown in the last row of Table II are attained. False positives no longer occur in the results, and a performance improvement can be observed over fixing $k=100$. An important observation is thus that the parameterization is individual to both the test candidate and the used beam width, thus a calibration may be inevitable, either a priori or on-line, i.e. during the course of a test.

Moreover, an important insight gained through revisiting the video recordings was that for $k=100$, in 12 out of the 24 attempts exactly one step too few had been counted. Even more, through the manual choice between $k=100$ and $k=50$, this happened in 20 out of the 24 recorded cases. We have identified (and later fixed) the reason for these errors: Our investigations have shown the root cause to be in the start trigger for recording gyroscope traces. As highlighted in a sample recording shown in Fig. 9, the characteristic peak of the first step is missing from the data. The reason was identified as the transmission delay of the start panel light barrier's state change. Combining the delays for its change detection, processing, and network transmission, several (potentially important) gyroscope samples are skipped before active sampling begins. By constantly writing measurements to a buffer and including about 0.2 s of these historic data in the analysis time series, the effect could be mostly mitigated, yet no more test subjects were available to verify the impact of this modification.

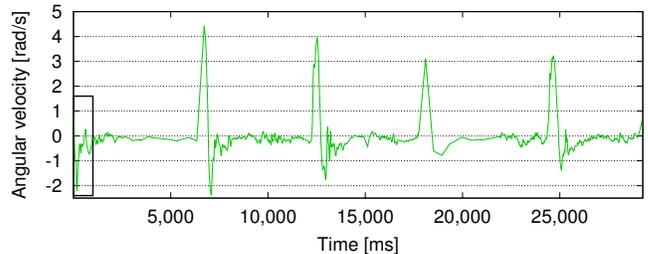


Fig. 9. Trace suffering from the delayed recording of gyroscope data due to the late arrival of the corresponding light barrier signal; as a consequence of this delay, the positive peak at the beginning of the trace was missing, and only the negative excitation following the positive peak has been captured.

VI. CONCLUSION

Motor performance ability is a key indicator for human health and wellbeing. Tests to determine MPA levels are, however, mostly based on the manual observation of candidates. The unavailability of automation severely hampers scalability and thus testing at large. In an attempt to mitigate these limitations, we have presented an embedded sensing system design based on gyroscopes and light barriers. Besides providing a solution to automate the step counting required for the “balancing backwards” test, our system design can also serve as the technological foundation for other locomotion-related MPA tests. In comparison to related work, our approach is robust against a wide range of external influences and does not require accurate placement of the sensing systems. Our practical evaluations have shown that the given motor performance ability test can be largely automated through our system design, leaving merely the identification of the subject and the score tracking to the examiner.

We have also identified potential for improvement, namely a more extensive investigation of the window size parameter k (or ways to meaningfully combine two or more values), which we intend to tackle in future work.

ACKNOWLEDGMENTS

We would like to thank the test subjects for their participation in our experiments. Moreover, we thank Daniel Şerbu and Malte Mues for their support.

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