

mBalance: Detect Postural Imbalance with Mobile Devices

Céline Madeleine ALDENHOVEN^{a,1}, Lara Marie REIMER^{a,b,2} and Stephan JONAS^b

^a Technical University of Munich, Garching, Germany

^b University Hospital Bonn, Bonn, Germany

Abstract. Background: Postural imbalance can be adopted for the early detection of age-related diseases or monitoring the course of the disease treatment; especially in monitoring, frequent balance measurement is crucial. This is mainly done through regular in-person examinations by a physician currently. Feedback in between examinations is often missing. Objectives: This paper proposes mBalance, a mobile application that uses the Romberg test to detect postural imbalance. mBalance provides a camera-based, low-cost approach to measure imbalance frequently at home using mobile devices. Methods: Imbalance detection accuracy and usability was evaluated in two separate studies with 31 and 30 participants, respectively. Results: mBalance correctly detected imbalance with a sensitivity of 80% and a specificity of 87%. The study found good usability with no significant problems. Conclusion: Overall, this study solves the problem of postural imbalance detection by digitizing a validated balance test into an easy-to-use mobile application.

Keywords. mHealth, Mobile Applications, Augmented Reality, Telemedicine, Postural Balance

1. Introduction

Postural imbalance occurs in several diseases and can be an early indicator. It is also useful for progress monitoring, severity assessment, and prognosis. According to Hugues et al., "**Stroke** frequently results in balance disorders" [1]. Balance has also been studied with **Parkinson's disease** [2, 3, 4]. Weiss et al. suggest using the balance test results as an additional and objective measure for tracking the progression of the disease and for supporting its treatment [5]. Melillo et al. pointed out the importance of balance detection in a non-clinical environment for **Multiple Sclerosis** patients to identify the severity of postural imbalance during a clinical checkup [6]. **Cognitive impairment, brain tumors, or injuries** can also lead to postural imbalance [1, 7, 8, 9, 10].

Furthermore, postural imbalance is often linked to an increased risk of falling, which is a common cause of death and disability in older adults [11]. Tracking postural imbalance progress in older adults can help doctors identify interventions to help increase the patient's balance most effectively and thus, reduce falls risk. Identifying balance high-risk falls behaviors is crucial for older adults' health and to destress the health care system. Additionally, assessment methods are necessary to implement preventative measures effectively [12]. Heitmann et al. found that women with a history of falls

¹ Corresponding Author: Céline Madeleine Aldenhoven, E-Mail: celine.aldenhoven@tum.de

² Corresponding Author: Lara Marie Reimer, E-Mail: reimer@tum.de

performed significantly worse in the balance tests than non-fallers [13]. Roeing shows that mobile balance detection is promising as smartphones can distinguish between high- and low-risk older adult fallers [14].

Postural imbalance assessment is usually performed during a medical examination to give the physician a snapshot of the patient's current condition. Other allied medical professionals, such as physiotherapists, occupational therapists, and sports scientists, administer balance assessments as well. The Romberg test is commonly used in the clinical field to measure static balance [15, 16, 17]. This test measures the subject's balance while standing straight with eyes opened and closed. Response is scored by noting the amount of time balance is maintained in this posture. Patients must track their balance at home for balance tests that require extended periods, which is often subjective. An easy-to-use mobile application that enables patients to conduct accurate balance tests at home changes this.

Even though postural imbalance detection is essential in early disease detection and progress supervision, no mobile application exists yet that allows patients to detect postural imbalance early or supplies doctors with balance data to track the progress of their treatment. Modern smartphones are equipped with various sensors, including optical and inertial. This enables new, accessible and low-cost clinical balance measurements [18]. Research shows that detecting postural imbalance through sensors integrated into mobile devices, i.e., accelerometers, is feasible. Galan-Merchant et al. used the accelerometer of an iPhone 4 to analyze the kinematics of the Romberg test between frail and non-frail older adults [19]. Fleury et al. developed a system included in a smartphone to help the user keep balance using audio-biofeedback [20]. Galan-Merchant et al. stated that the integrated inertial sensors in an iPhone 4 are sufficiently reliable and accurate to evaluate and identify kinematic patterns in balance tests [21]. Ozinga et al. used iPads to show that mobile devices provide an accurate and reliable data output to quantify the balance of Parkinson's disease patients [22, 23]. Overall, the accelerometer is the most used sensor in literature that assesses balance and human motion [5, 24 – 28].

While using the accelerometer of a mobile phone is convenient for conducting the Romberg test, it cannot provide any insights into whether the test was performed correctly. This is because there is no indication of whether a person was standing in the correct position or even standing at all. A more detailed balance analysis is possible through video-based motion tracking [29]. For example, Romaniszyn et al. [27] studied a marker-less, video-based balance state estimation of older adults. Another example is a low-cost, video-based tool performing clinical gait analysis using a marker-based gait assessment with five markers on the most important landmarks of the leg [28].

Our research is an essential step in moving clinical tests to mobile devices. We propose *mBalance*, a video-based mobile application that uses augmented reality body tracking to perform and evaluate the Romberg test. *mBalance* enables users to perform a balance assessment at home, and can be used to provide frequent feedback to their supervising physicians. The application guides the user through the assessment and validates the correct execution through video recording.

We performed two studies. In **validation study I**, we evaluated the detection accuracy of the augmented reality body tracking approach. The **usability study II** analyzed the app's usability, following the thinking aloud method by Nielsen [30].

2. Methods

2.1. The *mBalance* Application

The goal of *mBalance* is to provide an easy-to-use mobile application to perform the Romberg test at home. The app uses an iPhone or iPad and the ARKit framework for computer-vision-based pose detection of the human body. First, a user is guided through the test instructions (Figure 1a). The app will then automatically detect the patient's position (Figure 1b). Loss of balance, meaning leaving the test position, can also be detected. Furthermore, the app allows progress monitoring (Figure 1c-d).

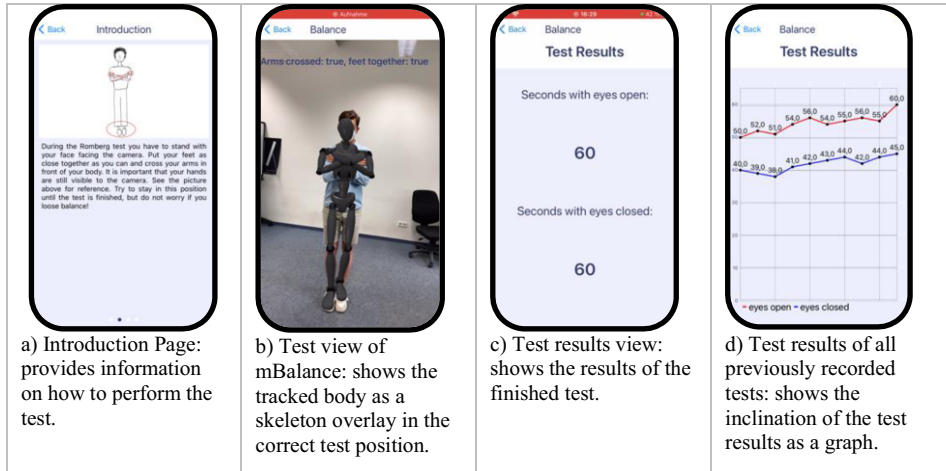


Figure 1. Main screens of the *mBalance* application.

mBalance conducts the Romberg test according to the specifications by [16, 19], with the arms crossed in front of the chest and feet together. The test is performed twice, once with open eyes and once with closed eyes. Each test run takes a maximum of 60 seconds. After the first test run, the patient is instructed to close their eyes and repeat the test via audio commands. If the patient loses balance in one of the test runs, time is stopped. Assessment continues with the second run or completion of the balance test. The test results are given in number of seconds for open and closed eyes with a result of 60 seconds indicating no balance impairments.

In *mBalance*, the detection algorithm recognizes whether the subject is standing in the correct test position or losing their balance by calculating the difference between the hand and feet coordinates. The origin of ARKit's body coordinate system is the pelvis center. The x-Axis is aligned through the pelvis with positive coordinate values toward the right side of the pelvis, and negative coordinates toward the left side. The y-Axis is aligned toward the head, with positive values toward the direction of the head and negative coordinates toward the feet in a standing position. The z-Axis is perpendicular to the pelvis and the vector between the pelvis and head. The coordinate system changes its orientation based on the movement of these landmarks. The *mBalance* algorithm calculates the correct hand position based on the distance between hands and feet based on this coordinate system. It additionally verifies that the hands are in a crossed position, meaning that the left hand is on the right side of the root coordinate and the right hand is on the left side.

The correct detection of the body and the extremities of ARKit can be affected by several reasons: Bad lighting conditions, hidden parts of the body, or the camera position, which is a known issue for computer vision-based motion capture systems [31]. We filter out poses where the algorithm detected position change for less than q seconds, assuming that this was a wrongly detected movement, to improve accuracy as this could otherwise lead to an erroneous balance detection result. The parameter q depends on the device's performance, as ARKit benefits from higher processing power and should be adapted to the device used. The value q has to be adjusted just right, as a higher q can result in a noticeable delay of balance loss detection, while a smaller q could incorrectly detect a loss of balance.

In the pre-tests of the study, we empirically determined the thresholds for verifying the test position detection and the parameter q by calculating the mean values for a correct detection based on the test data. The code was adapted accordingly to run on an iPad Pro (11" version, 2021, Apple Inc, Cupertino, USA). Our application's code can be found on GitHub³ to support future research.

2.2. Participants, Study Setting, and Data Processing

The validation study **I** and usability study **II** included 31 participants (5 female) and 29 participants (4 female) without balance impairments, respectively. The participants were between 19 and 56 years old. The balance of the subjects was tested before the study. Due to technical difficulties, one dataset was excluded in each study, leading to 30 and 28 usable datasets for the two studies, respectively.

In validation study **I**, each subject conducted the balance test three times; two times while keeping their balance and one time while intentionally losing balance. The subjects could randomly choose when and how often to lose their balance by taking a step, opening their arms, or both. Each subject was instructed before the study started on the correct test position, with feet together and hands crossed and visible to the camera. The tests were conducted on an iPad Pro 11 (M1 chip, LiDAR sensor). The iPad was placed on a tripod and kept at the same distance and height for all subjects. The participants stood close to a white wall, and wore tight clothes to increase body detection accuracy. The study conductor assessed whether the test results for each participant was detected correctly by *mBalance*. A true loss of balance was determined by the study conductor if the participants left the test position through opening their arms or taking a step; otherwise, no loss of balance was indicated. We quantitatively analyzed the results.

For study **II**, the participants were interviewed on-site using the thinking aloud technique [30]. The subjects were told: “*This app conducts a balance test. Your goal is to do the test once.*” No further information was provided. The subjects used an iPhone SE (2nd Generation, Apple Inc, Cupertino, USA) and a tripod. We grouped similar answers into categories (Table 1) and qualitatively analyzed the feedback.

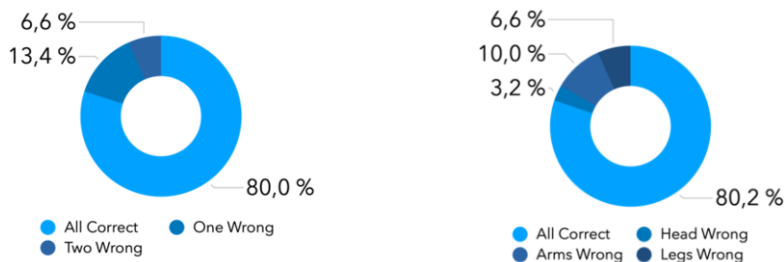
³ <https://github.com/dhg-applab/mBalance>

Table 1. The feedback categories for the usability study, grouped into feedback concerning the test setup ((1)–(5)) and the content of the *mBalance* app ((6)–(8)).

Category	Definition
(1) Correct test position	The subject has correctly placed themselves with arms crossed, hands still visible, and feet together in front of the camera.
(2) Correct camera position	The subject correctly used the rear-facing camera.
(3) Placed phone after introduction	The subject read all the introduction pages before placing their phone on the tripod.
(4) Distance to camera clear	The subject did not ask any questions about the distance that they should have to the camera.
(5) Phone position clear	The subject did not have questions about placing the phone horizontally or vertically.
(6) Understood swiping	The subject correctly understood the swiping process in the introduction pages.
(7) Intro test is understandable	The subject had no complaints about the test on the intro pages.
(8) Pictures are helpful	The subject did not have any recommendations about the pictures displayed on the introduction pages.

3. Results

In validation study **I**, *mBalance* detected all three consecutive measurements correctly for 66% of all participants. Detailed results are presented in Figure 2.



a) The percentages of whether the subsequent balance tests of one participant have been detected correctly.

b) The percentages of whether all losing balance tests have been detected correctly and, if not, which body part has not been detected correctly.

Figure 2. Different metrics regarding the detection rates of the balance tests using *mBalance*.

The contingency table indicates good performance (Table 2). Newer technology increases the precision of body detection, as body detection works better with the iPad 11 Pro than on the iPhone SE. The biggest reason for failed tests was false detection of the hands or feet once detection failed because the subject turned their head. This led to a rotation of the body model, which failed to correctly detect the hands and feet position. This is a problem contained in the ARKit framework.

Finding 1: *mBalance* can measure balance following the Romberg test with good precision. Limitations of the underlying technology caused most errors.

Table 2. Contingency table of the validation test of the *mBalance* application.

		Balance Test Outcome		
		Balance Loss	No Balance Loss	Total
mBalance Result	<i>Lost Balance Detected</i>	24	8	32
	<i>Held Balance Detected</i>	6	52	58
	<i>Total</i>	30	60	90
	*Sensitivity = $24 / 30 = 0.8$, specificity = $52 / 60 = 0.87$.			

Results from the usability study **II** (Table 3) indicated that subjects that did not position themselves correctly (1) either by not putting their feet together perfectly or crossing their arms but did not show their hands. As a high percentage of people positioned themselves correctly, this indicates the suitability of the introduction page. The most important finding in this usability study was the distance that the participants should have the camera (4) was unclear to 37.9% of the subjects.

Finding 2: Providing users with clear and concise instructions on how to position their phones and themselves is crucial for the test's success.

Participants who did not understand the swiping process immediately (6) commented that a “next” button would be beneficial. The subjects (17.2%) were bothered by the amount of text on the introduction pages (7). Most of them suggested using bullet points or animated videos. The pictures that have been shown in the introduction (8) were considered helpful by 93.1%. One thing which could improve the pictures was the ability to zoom in the images for a better view.

Finding 3: Using short and well-ordered descriptions and visualizations should be preferred over detailed textual descriptions as an introduction for the user.

Table 3. Results of the usability study for the different feedback categories are presented in Table 2.

Category	% of Participants	Category	% of Participants
(1) Correct test position	75,9%	(5) Phone position clear	90%
(2) Correct camera position	82,8%	(6) Understood swiping	89,7%
(3) Placed phone after introduction	69%	(7) Intro text is understandable	82,8%
(4) Distance to camera clear	62,1%	(8) Pictures are helpful	93,1%

4. Discussion and Future Work

4.1. Limitations

Both studies **I** and **II** had a small study group of 31 and 29 participants, respectively, leading to non-representative statistics. This limited group size was necessary due to COVID-19 restrictions. Additionally, *mBalance* is a limited application. There is room for complexity, like different variations of the Romberg test (sharpened, single leg), their specific consequences, and support for diagnosis.

In study **I**, everyone who participated was healthy. Therefore, the detection of balance loss had to be deliberately simulated, which differs from patients suffering from postural imbalance. Another study should be conducted on subjects with neurological disorders to assess *mBalance* with the target group. Our study was conducted under ideal

circumstances (good lighting, white wall on the background). In less than ideal conditions, human body detection might be challenging, which affects the accuracy of the app. In our validation study, we instructed all subjects on how to position themselves correctly. In the app's actual use case, more human subjects' errors need to be considered. Additionally, no security measures were implemented owing to the participants healthy balance state.

In study **II**, it is possible that subjects did not speak all their thoughts out aloud, even though this was encouraged. This would imply that the results presented in this research might deviate from reality.

4.2. Imbalance Detection Accuracy

To overcome current inaccuracies in Apple ARKit's body tracking, we selected a time interval q that determines whether a movement is caused by a body detection inaccuracy or an actual movement of the recorded person. This time interval was selected to fit the device's computing capabilities and its errors in detecting the human body to ensure the best performance of the application. In future work, this could be improved to ensure transferability to other devices, for example, by applying filters to the signals emitted by ARKit.

In our study, *mBalance* achieved good results for state-of-the-art research in digital health. This implies that we can enable patients to test themselves at home, even though mobile body detection is still error prone. This would allow patients to perform regular assessments easily and monitor their balance, leading to early detection of any change.

4.3. Usability Discussion

Most of the participants positioned themselves correctly, but this could be improved by highlighting the explanation of the test position during the introduction. Another way to ensure the correct position is to enhance the pose detection algorithm. The accuracy of the pose detection is currently highly influenced by parameters like background and lighting, which require filtering of the motion data. While the performance of the ARKit framework presently limits this, it could be an option for future research projects with other technological approaches or newer technology.

It is essential to tell the user when they are recognized to indicate whether they positioned themselves at a sufficient distance to the camera. However, ARKit still recognizes people even when they are not entirely in the camera frame by calculating the missing coordinates, which might influence the correct balance test result. This could be addressed by providing them with a concrete number of steps they need to walk away from the camera to perform the test during the introduction or automatically calculate whether the calculated coordinates are within the visible coordinate system of the camera. Surprisingly, over 60% of the subjects had no problem with this issue. However, ensuring an adequate distance between the camera and the tracked subject should be addressed in further research.

4.4. Future Work

Our research focused on evaluating the feasibility of balance detection using optical motion tracking methods like Apple ARKit.

The Romberg test includes further variations which should be considered in future implementations of the mobile Romberg test. These include asking the subject to raise their arms in front of them and to gently “push” the subject in different directions, to assess how their balance reacts to external disturbances. Other possible extensions to *mBalance* are balancing in step stance, tightrope stance, or single leg stance. *mBalance* could be further extended by dynamic balance scales like the Berg Balance Scale, which is a commonly applied balance test battery in rehabilitation and falls prevention.

mBalance is currently intended for patients with mild balance impairments as no security measures were implemented. Future work should focus on testing its accuracy with safety measures like having supporting persons next to them to prevent falls in more severely impaired individuals.

5. Conclusion

mBalance suggests using augmented reality body tracking for in-home postural imbalance detection using commodity hardware like smartphones and tablets. The *mBalance* app showed good usability and accuracy of measurement. Even though the underlying technology exhibits inaccuracies in tracking the human body through a smartphone's camera, the approach enables new possibilities of remotely supervising patients and thus, gaining better insights into their health status between appointments. Future work should focus on improving the accuracy of the imbalance detection, and evaluate the approach in a clinical setting.

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