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Motion Signal Processing in Heel Rise Tests Applied to Older Adults

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Abstract. The aging of the global population is a growing reality. It is estimated that the number of people over the age of 60 will reach 2 billion worldwide by 2050. In older adults, the muscular function of the triceps surae plays a central role in postural control and functionality, being essential for maintaining balance and mobility. Reduced performance of the plantar flexor muscles has been associated with loss in functionality, decreased quality of life, and an increased risk of falls, making the assessment of this muscle group crucial. In this context, the Heel Rise Test (HRT) has been used to evaluate strength and endurance. Traditional assessment methods for this test are based on visually counting repetitions, which may lack accuracy. Moreover, the identification of other relevant movement parameters, particularly those related to the time and frequency domains, is often overlooked. On the other hand, inertial sensors embedded in smartphones represent a promising alternative for quantifying translational acceleration and angular velocity signals, given their low cost and large accessibility. However, the use of such signals requires caution, as double integration of acceleration signals to obtain displacement data may lead to cumulative errors, known as integration drift. This study presents the development of a reliable and effective numerical procedure for processing inertial sensor signals from smartphones during the Heel Rise Test. The results obtained through the proposed procedure are compared to those acquired simultaneously by using a reference method (in this case, a video camera), ensuring concurrent validity. It is verified that the proposed procedure provides sufficiently accurate measurements, enabling the extraction of relevant information about the muscular function of plantar flexors in clinical settings. It is understood that access to reliable and easily obtainable data can positively impact the diagnosis and monitoring of the target muscular function, supporting strategies aimed at reducing the risk of falls and improving quality of life in older adults.

Keywords: calf raise; inertial sensors; integration drift; smartphone.

1 Introduction

The heel rise test (HRT), also known as the calf raise test (CRT), is widely employed in both clinical practice and research settings to assess the strength and endurance of the plantar flexor muscles, particularly the triceps surae [1]. Its simplicity makes it suitable for a variety of contexts, ranging from rehabilitation to the monitoring of frailty in older adults and individuals with Parkinson's disease.

In recent years, inertial measurement units (IMUs) have emerged as a promising alternative to traditional laboratory-based technologies, such as force platforms and motion capture systems [2]. Due to their portability, affordability, and non-invasive nature, IMUs enable functional assessments to be conducted even outside of clinical environments. However, their use is constrained by technical challenges—most notably, the issue of integration drift, which arises from the double integration of acceleration signals to estimate position or displacement.

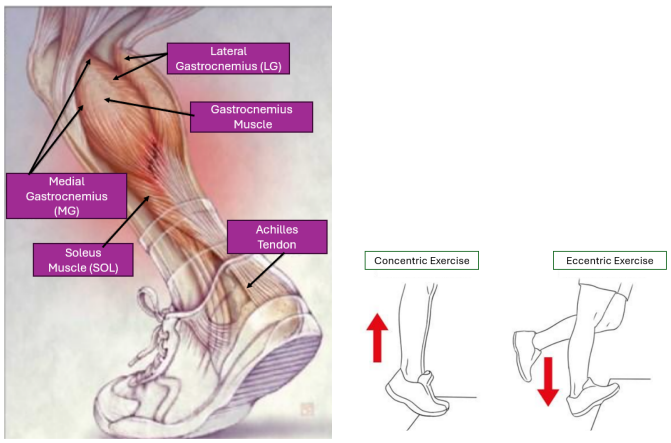
This study specifically addresses this challenge by proposing a methodology to mitigate the effects of integration drift when using inertial sensors during the heel-rise test. By tackling this limitation, the aim is to enhance the reliability and clinical applicability of IMUs inside smartphones in routine practice.

2 The Heel-Rise Test (HRT): Terminology and Applications

The heel-rise test (HRT) appears under various names in the literature. It is also referred to as the calf raise test (CRT), up on toes test (UTT), UTT-30, and calf rise to squat, among others. This broad terminology reflects

the wide range of movement patterns and characteristics that can be extracted from the test when it is performed properly.

The heel-rise test is one of the most widely used functional assessments in both clinical practice and research for evaluating the function of the muscle-tendon unit (MTU) of the triceps surae, particularly in terms of strength and endurance. The triceps surae (TS) consists of the soleus (SOL), medial gastrocnemius (MG), and lateral gastrocnemius (LG) muscles (see Figure 1a), which share a common insertion on the calcaneus via the Achilles tendon [3]. The triceps surae muscles are responsible for approximately 80% of the plantarflexion torque. In addition, several intrinsic and extrinsic foot muscles contribute to the stability and function of the foot during weight-bearing activities.



(a) (b)

Figure 1. Active muscles during the test

The heel-rise test requires individuals to raise their heels off ground and lower themselves as many times as possible while standing, performing repetitive concentric and eccentric actions (see Figure 1b) of the ankle plantar flexors for a duration of 30 seconds[1]. It can be performed using a single leg (unilateral, as shown in Figure 2a) or both legs simultaneously (bilateral, as shown in Figure 2b).



(a) Single Leg (b) Double Leg / Bilateral

Figure 2. Test Protocol

3 Inertial Measurement Units (IMUs)

Inertial measurement units (IMUs) have emerged as an innovative and non-invasive solution not only for assessing athletic performance but also as a clinical tool for evaluating functional capacity. This advancement is particularly relevant in the context of frailty in older adults and individuals with Parkinson's disease, where patient displacement to clinical settings may be discouraged. In fact, sophisticated and high-cost measurement technologies, such as force platforms and vision-based systems, have increasingly been restricted to laboratory environments.

One of the main limitations of IMU sensors is that their output signals consist of relative data, such as intersegmental angles and accelerations, whereas standard technologies directly provide the position of a body segment within a fixed reference frame. Determining the three-dimensional position of a segment, absolute angles,

[1]The HRT has a duration of 30 seconds.

and full-body kinematics still remains as one of the greatest challenges when using body-worn inertial sensors [4]. In this context, one of the most recurrent issues is the integration drift effect, which arises during the integration of acceleration signals to obtain velocity or position, and may even obscure the true outcomes [5].

Several approaches have been explored in the literature to partially mitigate this issue: sensor fusion or auxiliary systems [6], Fourier-based filters [7], band-pass filtering [8], and polynomial curve fitting [2]. In general, these methods rely on the assistance of externally referenced sensors or prior knowledge of the movement, as well as linear and adaptive filtering techniques, or other data processing strategies to estimate displacement from acceleration signals.

4 Materials and Methods

The inertial sensor embedded in a smartphone provides acceleration measurements, whereas the camera supplies position data. Therefore, to enable a meaningful comparison between these sources, it is necessary to integrate the acceleration signal, or differentiate the position record.

The process of acceleration integration, of concern herein, results in cumulative error, commonly referred to as integration drift. To mitigate this error, the following procedure is proposed:

- Pre-processing:
  1. The sampling frequency of both signals is calculated;
  2. When the sampling frequency is not constant, the data is resampled using the `resample` function in MATLAB;
  3. The IMU and camera signals are filtered, to remove unnecessary information;
  4. The signals at the start and end points are trimmed, to process meaningful data.
- Processing:
  1. The acceleration signal's mean is computed;
  2. The signal is adjusted by subtracting its mean from the original data;
  3. Numerical integration on the adjusted signal is performed;
  4. The trend line of the integrated signal is determined;
  5. The trend line is subtracted from the integrated signal, to obtain the integral without accumulated error.

  Once the first integration is successfully completed, the process can be repeated. However, since the initial condition of the position is known above [2], the algorithm should be slightly modified as follows:
  1. The numerical integration of the velocity signal is performed;
  2. A spline is determined based on the signal's minimum points instead of computing a trend line;
  3. The spline is subtracted from the integrated signal to obtain the position without accumulated error.
- Post-processing:
  1. The x-axis alignment of the displacement graph—obtained through double integration—is adjusted using the camera signal as a reference (regarded, then, as a gold standard).

The results obtained from processing the signals collected by smartphone inertial sensors can be compared with the outcomes derived from camera footage during the HRT. In this comparison, root mean square error (RMSE) values are calculated for evaluation purposes.

In this work, the above procedure was implemented to process the measurements made with two smartphones Apple iPhone 13 Pro, model A2638. One device was used to collect the IMU signal, while the other acquired the video record. The HRT was applied to a single individual, following the same conducts specified in [9]. The IMU signal was retrieved by the SensorLog software and the camera record by the Kinovea software.

5 Presentation and Discussion of Results

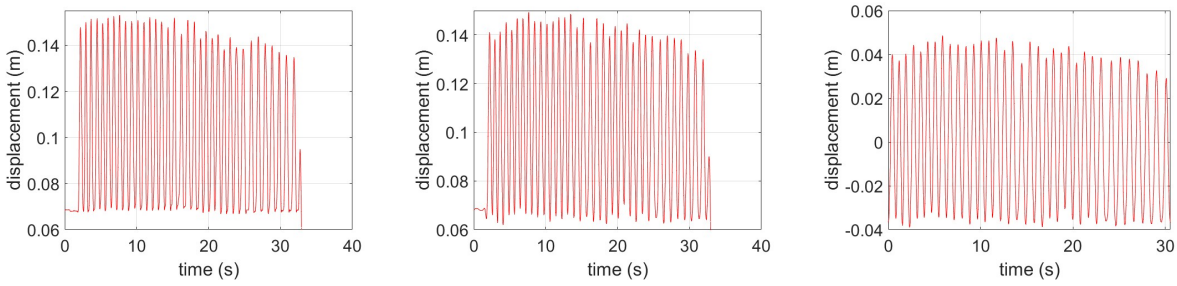
In this section, the results obtained from the pre-processing, processing, and post-processing stages are presented and analyzed.

5.1 Signal Pre-processing

The sampling rate of a smartphone sensor is usually variable. For the smartphone sensor, the interpolation procedure described in Section 4 was applied using the `resample` function in MATLAB, with the objective of obtaining a constant sampling frequency. The same frequency as the camera was chosen to simplify the subsequent steps.

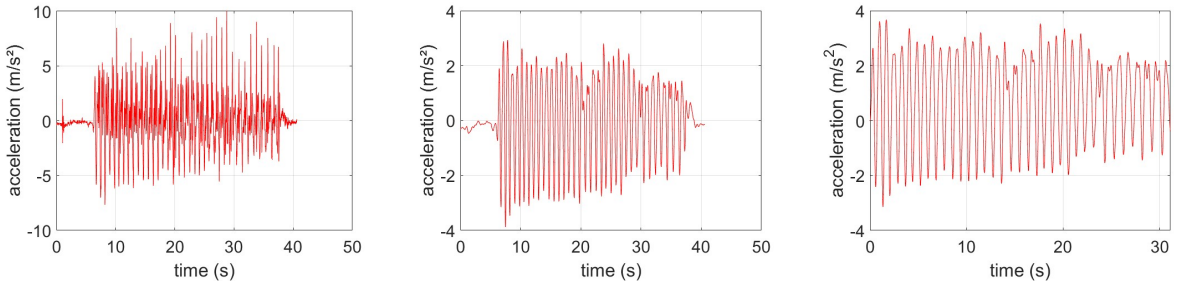
[2] Known initial condition: the position signal does not contain negative values (it is not physically possible to move below the ground level).

Next, as also described in Section 4, filtering was applied to the data (both from the IMU and the camera), followed by trimming. Figures 3 and 4 illustrate the signals before and after filtering and trimming.



(a) Unfiltered Camera Signal (b) Filtered Camera Signal (c) Trimmed Camera Signal

Figure 3. Filtering and Trimming of the Camera Signal



(a) Unfiltered IMU Signal (b) Filtered IMU Signal (c) Trimmed IMU Signal

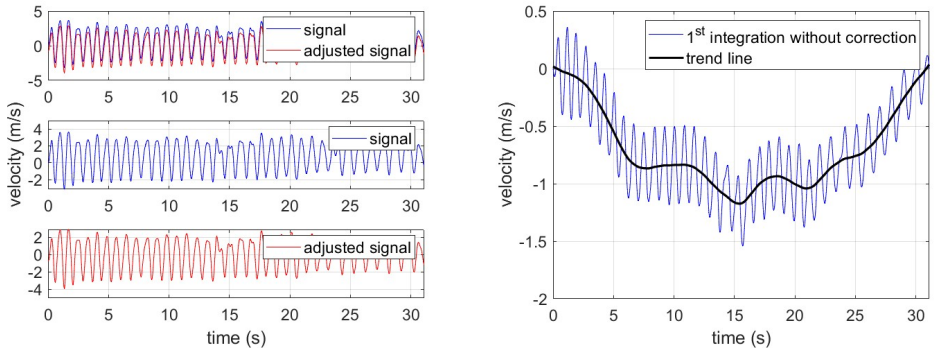
Figure 4. Filtering and Trimming of the IMU Signal

5.2 Signal Processing

After completing the pre-processing steps, the processing steps described in Section 4 were implemented with the goal of performing double integration of the acceleration signal obtained from the smartphone, aiming to minimize the drift error as much as possible.

- First Integration

Figure 5(a) illustrates the vertical alignment (mean-centering) of the IMU signal along the y-axis. Figure 5(b) shows the result of the first integration using the trapezoidal method, along with the trend line.



(a) Signal before integration, adjusted along the y-axis (b) Uncorrected 1st integral and trend line

Figure 5. Mean-centering and 1st Integral

By correcting the signal based on the trend line, the velocity signal (the first integral of the acceleration signal) is obtained in its corrected form. This signal is shown in Figure 6.

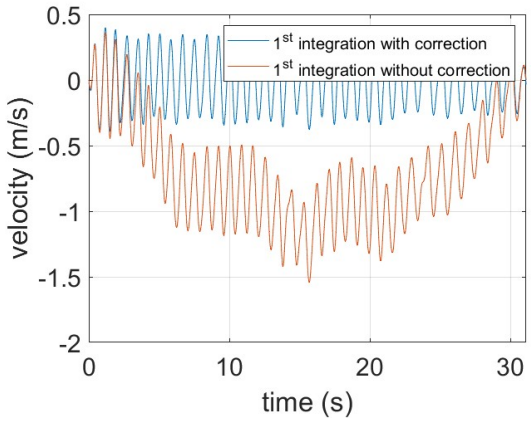
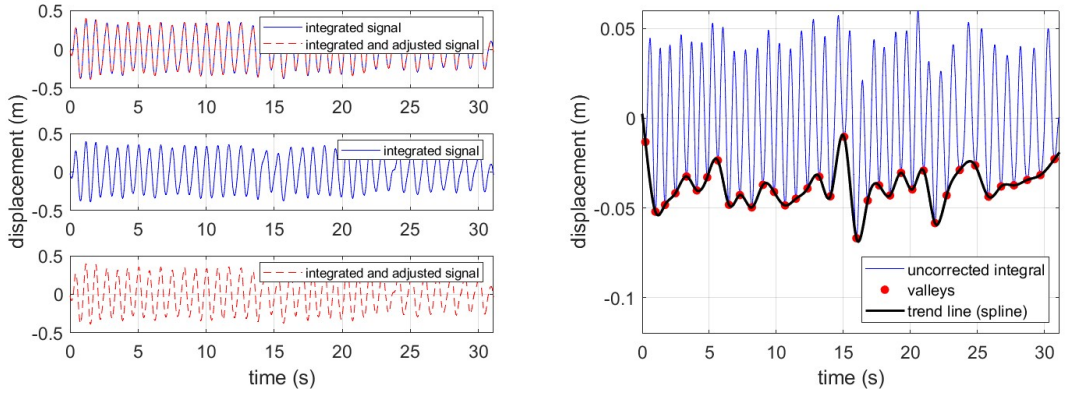


Figure 6. First integration of the acceleration signal after drift correction using the trend line

- Second Integration

As a precaution, the signals were once again mean-centered along the y-axis. Figure 7(a) illustrates this step. The second integration was also performed using the trapezoidal method. Figure 7(b) shows the uncorrected displacement resulting from the two consecutive integrations of the IMU acceleration signal, as well as the new trend line.

In the second integration, the trend was removed using a `spline` function for MATLAB, instead of a linear fit. Figure 8 illustrates the corrected displacement derived from the y-axis acceleration signal obtained via the smartphone's IMU sensor.



(a) Signal before the 2nd integration, adjusted along the y-axis

(b) Uncorrected 2nd integral and trend line (spline)

Figure 7. Mean-centering and 2nd Integral

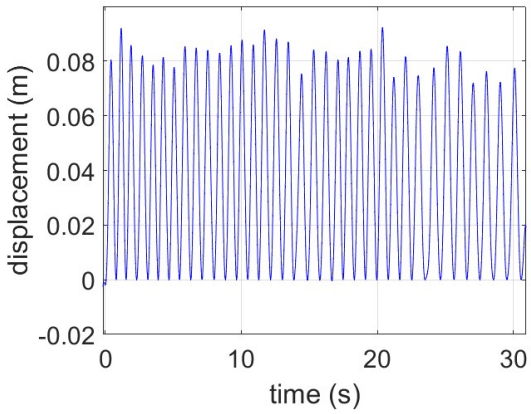


Figure 8. Displacement obtained by double integration of IMU acceleration signal

5.3 Signal Post-processing

Figure 9 presents the displacement signal obtained from the camera along with the displacement signal obtained through double integration of the acceleration signal from the smartphone's IMU. In this figure, the camera-based displacement signal was shifted along the x-axis to ensure consistency in the comparison.

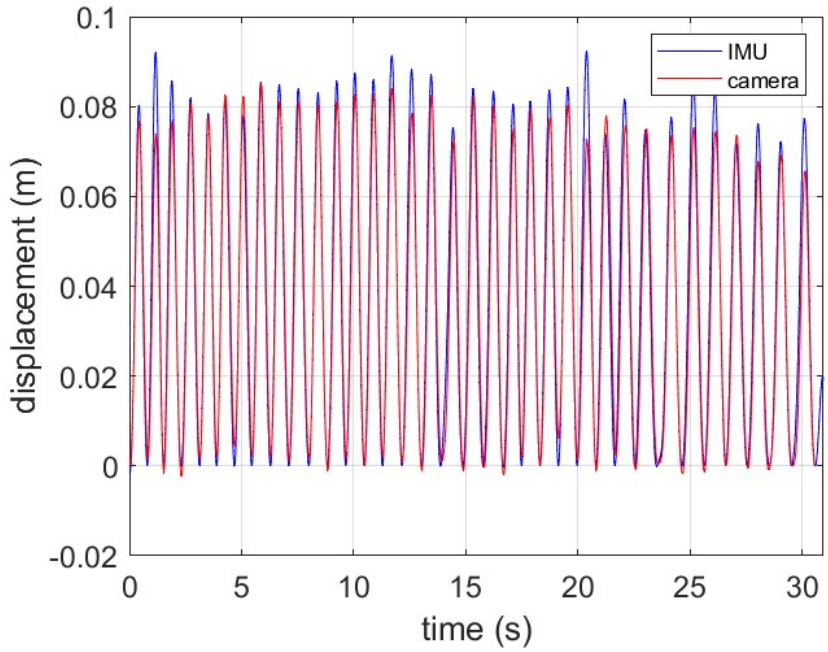


Figure 9. Comparison between displacement records obtained by camera and by IMU (after double integration and drift removal)

In the comparison between the two signals, $y_{\text{IMU}}(t)$ and $y_{\text{cam}}(t)$, the difference between them was quantified using the root mean square error (RMSE), after temporal alignment. The camera signal, $y_{\text{cam}}(t)$, was interpolated at the time instants of the IMU signal, t_{IMU}, resulting in $y_{\text{cam}_{\text{interp}}}(t_{\text{IMU}})$. Next, the RMSE value was calculated only for the points within a common time interval, in order to avoid issues with undefined values (NaNs).

The formula used to compute the RMSE is given by

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{\text{IMU}}(t_i) - y_{\text{cam}_{\text{interp}}}(t_i)\right)^2} \tag{1}$$

where

- $N \rightarrow$ number of points within the common time interval where both signals are defined;
- $y_{\text{IMU}}(t_i) \rightarrow$ IMU signal values at the time instants t_i;
- $y_{\text{cam}_{\text{interp}}}(t_i) \rightarrow$ interpolated camera signal values at the same time instants t_i.

The RMSE value obtained was

$$\text{RMSE} = 4.8 \text{ mm} \tag{2}$$

which corresponds to approximately 5.6% of the maximum amplitude of the displacement measured by the camera. Based on both the visual analysis of Figure 9 and the computed RMSE value, it is understood that the current signal processing is really effective for the intended purposes.

6 Conclusions

As the RMSE value is considered satisfactory for biomechanical data, it can be stated that the proposed method is effective. This approach may be a key step toward making motion analysis more accessible in real-world clinical environments, by use of widely available smartphones.

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