Step Length Measurement Through Signal Power Analysis and Accelerometer Device: A Laboratory Comparison

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Abstract: The monitoring and analysis of kinetic and kinematic parameters integrated into sports disciplines such as race walking can provide valuable information for developing personalized training programs and evaluating technique execution. In this study, we developed two systems for measuring step length based on microcontrollers ESP32. The first system is based on measuring the received signal strength between two antennas, while the second relies on inertial sensors (MPU-9250). Both systems were tested in a laboratory setting using a treadmill and video recording to assess their accuracy. The results showed that the system based on signal strength measurement exhibited low precision at distances within a range of a few centimetres. On the other hand, the inertial sensor-based system demonstrated higher accuracy when compared to video recordings. Although the measurements differed statistically between these two methods (p-value = 0.001), the proposed inertial system recorded a step length of 65 (61-69) cm, while the video recordings measured 67 (64-70) cm. The error distribution analysis showed that 39% of measurements had an error of 3.2 cm, 32% had an error of 7.5 cm, and 29% had an error not exceeding 12 cm. The proposed system shows potential for step length quantification using the MPU-9250 sensor; however, further testing is required to reduce the measurement errors.

1 INTRODUCTION

Race walking is a sport discipline that combines aspects of normal walking with specialized biomechanical techniques, characterized by the absence of a flight phase and the need for continuous contact of at least one of the lower limbs with the ground (Caporaso et al., 2020). Stride length and various factors, such as height, muscle strength, flexibility, time flight, and technique, converge and their analysis enables the identification of movement patterns, biomechanical alterations, and optimization of athletes' walking technique (Pavei et al., 2019; Barreto-Andrade et al., 2016).

The aforementioned parameters require that the technique necessitates rigorous monitoring and control, both in training stages and in field competitions, to optimize performance and prevent injuries. However, in addition to their complexity, the current tools available for measuring and analysing these biomechanical parameters are limited in accessibility, making their use in amateur training groups challenging (Taborri et al., 2019).

Studies involving kinematic analysis using high-speed cameras or force platforms face practical challenges in outdoor environments, mainly due to their high complexity in acquisition and setup. Although precise, these technologies are less accessible for real-world applications outside controlled laboratory environments due to their reliance on stable setups and detailed calibrations to ensure data accuracy. In (Bernardina et al., 2024), the feasibility of using action sports cameras for 3D motion reconstruction of swimmers

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both in air and underwater was explored, highlighting a more economical and flexible alternative to traditional motion capture systems.

From the perspective of portable solutions, the research conducted in (Zrenner et al., 2018) has demonstrated that using inertial sensors to measure running speed and stride length can be a practical and portable tool, such as *RunScribe* and *Garmin Running Dynamics Pod* that utilize accelerometers for data collection. *RunScribe* offers a device equipped with the InvenSense MPU-9255 motion sensor, which integrates a gyroscope, accelerometer, and magnetometer in a three-axis system. The inclusion of these technologies allows for the measurement of biomechanical variables such as ground reaction force (Lewin et al., 2022). Similarly, the *Garmin Running Dynamics Pod* uses an accelerometer to capture torso movement and measure key metrics like cadence, stride length, ground contact time, and vertical ratio (Drobnic et al., 2023). The rapid advancement of sensors and the reduction in manufacturing costs have driven the increasingly widespread use of technology in sports, encouraging its development and adaptation to specific training needs (Campoverde-Gárate et al., 2022; Flores-Morales et al., 2016; Cho, 2017; Mali and Dey, 2020).

Building on the difficulties exposed, this project assesses the viability of developing solutions for measuring stride length in race walking by comparing the use of inertial measurement sensors with the data provided by their accelerometers, and the measurement of power using the received signal strength indicator (RSSI) parameter through WiFi communication between two ESP32 microcontrollers.

Previous works proposes the use of RSSI for localization in both indoor and outdoor sports systems. In (Pricone and Caracas, 2014), they use RSSI to estimate distance through trilateration, adapting a path loss model with shadowing to adjust the signal strength received based on distance, which is essential for real-time tracking applications. In the study presented by (Ruiz Zambrano and Villalta Encalada, 2024), power measurement was evaluated as a tool to relate it to step length. However, the results indicated that the system was not suitable for short distances. Based on these results, we hypothesized that stabilizing the transmission power and improving temporal synchronization of transmitted values of power data between transmitter and receiver will provide more accurate results when measuring short distances.

The use of the MPU-9250, which integrates accelerometers and gyroscopes, enables gesture detection in various sports disciplines such as running, weightlifting, or race walking. (Cárdenas-Rodríguez et al., 2023; Mali and Dey, 2020; Flores-Morales et al., 2016).

Our study proposes to compare two methods for measuring step length: the method based on measuring the transmitted power between the emitter and receiver and the accelerometer-based method. Our objective was to evaluate both methods with the intention of developing, in the future, a system for monitoring step length in race walking as a tool for training monitoring in sports.

2 MATERIALS AND METHODS

2.1 Measurement Based on Power Transmission (RDU)

To conduct this research, a distance measurement system based on RSSI was first developed (RDU - RSSI Distance Unit), based in the measurement of the power level of a received signal, useful for distance estimation (Vikas et al., 2016). For distance calculation we used two ESP-WROOM-32 development board. For communication, the integrated IEEE 802.11 b/g/n WiFi module operates at 2.4 GHz, setting up the two ESP32 microcontrollers as an access point and a client as shown in Fig. 1 where the system operation is generally explained.

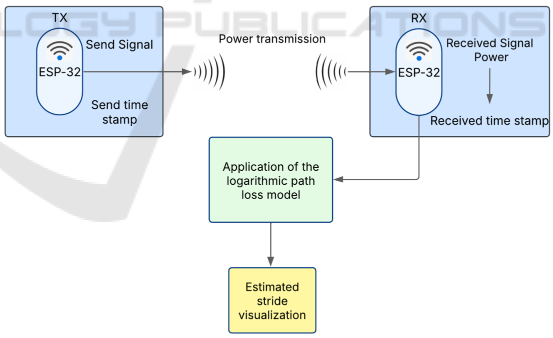

Figure 1: Diagram for communication between microcontrollers in the step length estimation system through transmission power measurement.

The microcontroller configuration process is detailed below:

- Terminal TX Configuration: An ESP32 microcontroller was configured as an access point, it creates a WiFi network with a predefined SSID (Service Set Identifier) and password to establish a secure communication link. It continuously transmits a preconfigured message with a timestamp corresponding to the moment the message is sent, ensuring a constant flow of data between devices.

- Terminal RX Configuration: A second ESP32 microcontroller was configured as a device that connects directly to the first microcontroller TX acting as a host using the assigned credentials to receive and process the messages. Its main functions include decoding the received message, extracting, and logging the RSSI value associated with the message.
- Communication: To enable communication, the client receives the message from the access point. This process ensures that the transmission time and transmission losses are recorded using the RSSI parameter for each instance of communication. The time interval between transmitted messages was set to 75 ms and the initial transmission power was set at -19 dBm as the upper limit to ensure a stable connection.

The distance estimation through the RDU system is based on the logarithmic relationship between signal intensity and distance (Wu et al., 2015; Moya Velasco, 2019). This model describes signal loss as a logarithmic function of distance with Equation 1:

$$P_l(d) = P_l(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\sigma, \qquad (1)$$

where n is a path loss factor, typically between 2 and 5, depending on the environment, X_σ is a random variable with a normal distribution, and d_0 is the reference distance, usually 1m. This model is suitable for outdoor applications due to its low cost and acceptable accuracy (Cao and Li, 2013).

To capture the data, measurement devices were placed on the subject's body (see Fig. 2). The RDU system was positioned at the front part of each shoe. Building upon the work presented in (Ruiz Zambrano and Villalta Encalada, 2024), we implemented in software a temporal synchronization stage to manage transmission of the measured power data. Synchronization was achieved by sending two parameters in an array: a timestamp and the corresponding RSSI value. Path loss was then determined by calculating the difference between transmitted and received power for each recorded value across the predefined time intervals.

Both of the systems (RDU and SIMPU) used a push-button placed at the bottom of the shoe, which helped synchronize data collection since the push-button is responsible for initiating the systems to collect data in a coordinated manner.

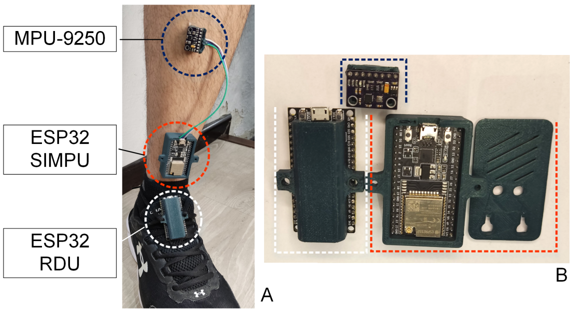

Figure 2: A: Positioning of the SIMPU (red dotted line) and RDU (white dotted line) systems mounted on one leg of the subject for treadmill testing. B: Image focused on the inertial sensor (blue dotted line) and microcontrollers for data management.

2.2 Measurement Based on Accelerometer (SIMPU)

At this stage of the project, we designed a system based on the MPU-9250 inertial sensor (SIMPU), which measures acceleration in three axes, allowing for distance estimation using the Attitude and Heading Reference System (AHRS) algorithm. Additionally, we included a Kalman filter to enhance the accuracy of these angles through data fusion and Bayesian estimation, considering both system and observation noise (Chunyang et al., 2015; Terán Pineda, 2017). This filter predicts the system state and then corrects it based on the observed measurements (Terán Pineda, 2017; Krishnaveni et al., 2022). The prediction equation is:

$$P_k = (I - K_k H) P_k^- \qquad (2)$$

Where P_k is the estimation error covariance after correction, I is the identity matrix, K_k is the Kalman gain, H is the observation matrix, and P_k^- is the predicted estimation error covariance.

The AHRS algorithm processes the corrected data from the MPU-9250 sensor to continuously estimate the device's orientation in real-time. This orientation is represented by Euler angles: roll (θ), pitch (ϕ), and yaw (ψ), which describe how the athlete's foot tilts and rotates during race walking (Wang et al., 2014; Madgwick, 2014), as seen in Fig. 3.

The MPU-9250 obtains these orientations from the integration of angular velocities provided by its gyroscope, as expressed in the following equation:

$$\text{Rotation Angle} = \int \text{angular velocity}\, dt \qquad (3)$$

However, due to the accumulation of drift errors in the integration process, the AHRS algorithm applies sensor fusion techniques, combining data from the accelerometer and gyroscope. This approach, optimized

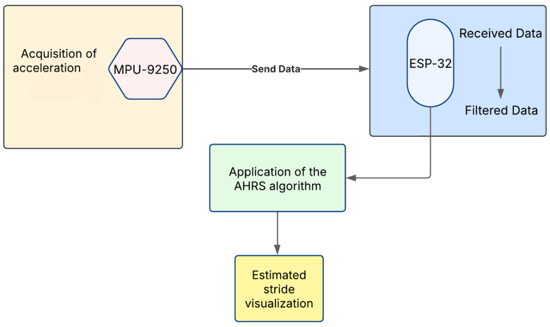

Figure 3: Block diagram of distance estimation based on accelerometer readings.

by Madgwick (Madgwick, 2014), corrects cumulative deviations, ensuring more accurate and stable orientation estimates, even during dynamic movements. The SIMPU system was affixed to the mid-part of the tibia to minimize possible tilts that could introduce disturbances into the inertial measurement system (see Fig. 2).

2.3 Laboratory Tests

Given the exploratory nature of this laboratory study, the assessments were conducted with a single participant (27-year old, height=1.81 m, and mass=105 kg). The subject was in good health, had no suffered recent injuries, and was fully informed about the scope of the project from the beginning and voluntarily agreed to participate. The subject was subjected to a race walking session on a treadmill in the Effort Laboratory of the Universidad Politécnica Salesiana, Cuenca Campus. For video recording, an smartphone camera was used (108-megapixels and 30 fps) and positioned parallel to the subject's plane of movement on the treadmill. For comparative evaluation, Kinovea software (v1.2, open-source, available at http://www.kinovea.org) was used, which allowed for an analysis of measurements in real time against video captures. Data from the RDU system, SIMPU, and video images were recorded, enabling cross-validation of the obtained results.

The RDU and SIMPU systems operate independently. For the RDU setup, the system is placed on the right ankle, as shown in Fig. 2, while a microcontroller is attached to the left ankle to record the received signal strength. For the SIMPU system, a single unit is positioned on the right ankle. Once the systems are in place, the subject walks on the treadmill, and when the target speed is reached, an external trigger is applied via a push button to synchronize both systems with the video recording.

The laboratory tests were divided into two stages. In the first stage, three sessions were conducted (one minute each one). The subject wore visible markers (white tape) on the key areas where devices were installed, which facilitated the correct identification of each system during analysis in the reference software. As a metric reference, a 1.5 m tape measure was used to calibrate the reference in Kinovea software. To avoid inconsistencies in comparing results, both systems (RDU and SIMPU) were evaluated simultaneously, ensuring that the measurements obtained reflect the same experimental context and allowing a direct and unbiased comparison.

In the second stage of testing, we discarded the system that exhibited the highest error and repeated the tests using only the remaining system. For the statistical analysis we used the Wilcoxon rank sum test to compare the medians of the registered data, after assessing data normality using the Kolmogorov–Smirnov test. This non-parametric test does not assume normality of the recorded step length measurements. The hypothesis test was based on the null hypothesis (H_0), which stated that the measurements obtained with our system were comparable to those recorded by video. A significant result (p-value$\leq$0.05) would indicate a difference between the two sets of measurements.

3 RESULTS

During the first stage of testing, a total of 133 steps were recorded, and the results analysis in this section was based on this data. The measurements recorded with both systems and the Kinovea software can be observed in Fig. 4A. Additionally, a description of these results is presented in Table 1, which includes the p-value obtained by comparing the results of the two proposed systems with those of the Kinovea software. In the comparative evaluation, we can observe that the measurements with the SIMPU system show a high level of similarity with the Kinovea records (p-value=0.350). On the other hand, the measurements taken with the REDU system are statistically different (p-value$<$0.001).

The measurements of each system were compared with the Kinovea record, and the absolute error is calculated for each measurement. Fig. 5 shows the error distribution for the SIMPU and RDU systems. It can be observed that the SIMPU system exhibits a more concentrated error distribution with less dispersion around zero, indicating greater precision and less variability in its measurements. In contrast, the RDU system shows a wider distribution, with scattered errors and a higher frequency of elevated values, suggesting lower accuracy and greater variability in data

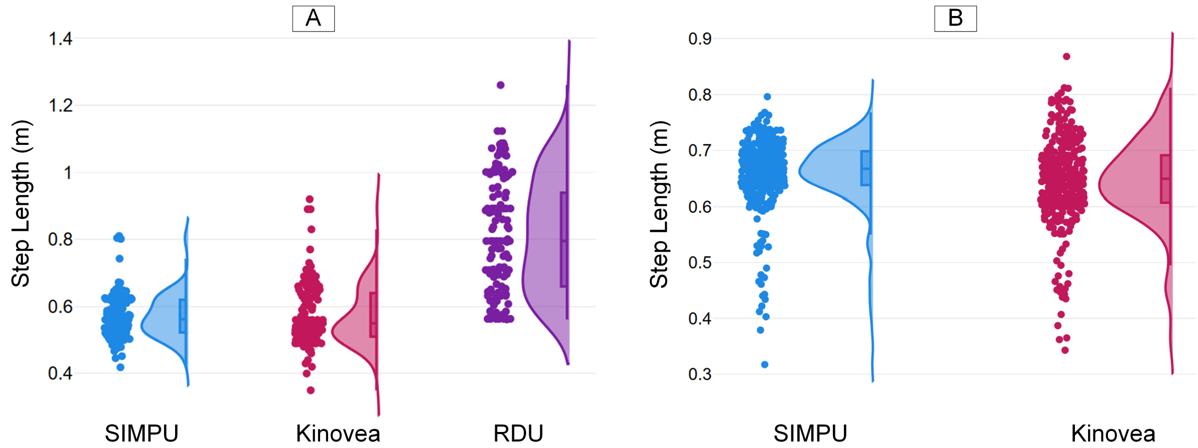

Figure 4: A: Box plot comparing the distribution of step length measurements between SIMPU, RDU, and Kinovea software in tests stage 1. B: Comparison of step length measurements between SIMPU and Kinovea in the test stage 2.

Table 1: Description of the data obtained by the SIMPU and RDU systems in meters (m). The median value and interquartile range are presented. The RMSE and the p-value shown was calculated by comparing the results of each system with those obtained from Kinovea.

System	**Step Length**	**RMSE**	***p*-value**
First test			
Kinovea	0.56 (0.52 - 0.62)	-	-
SIMPU	0.55 (0.51 - 0.64)	0.057	0.350
RDU	0.80 (0.66 - 0.94)	0.299	<0.001
Second test			
Kinovea	0.67 (0.64 - 0.70)	-	-
SIMPU	0.65 (0.61 - 0.69)	0.045	0.001

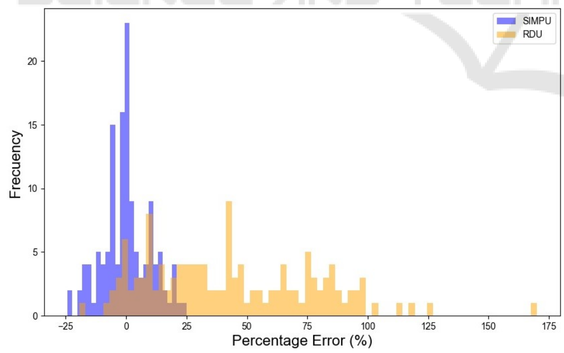

Figure 5: Calculation of the absolute error of the measurements with the proposed systems compared to the Kinovea measurements.

measurement.

The data obtained, which contrast the readings of the systems with the reference measurements from Kinovea software, indicate that the SIMPU system exhibited statistically similar, as evidenced in Fig. 4A. The values for the SIMPU system remain within a narrower and more predictable range compared to those of the RDU system, which shows considerable variability and a lack of a clear pattern of behavior. The more centred median and narrower range in the SIMPU data compared to the RDU data (see Table 1) reinforce the idea that SIMPU is more stable and reliable for these measurements. The RMSE value between SIMPU and Kinovea was 0.057 m, indicating a small average error between the measurements.

For the second stage of testing (304 steps recorded), measurements were conducted exclusively with the SIMPU system in the same laboratory and under identical test conditions. The step length results were incorporated into Fig. 4B. for comparison, while the median and interquartile range results were added into the lower section of Table 1. The results show an maximum error of 20%, similar to that obtained in the first stage of testing. However, when statistically comparing the results, we observe a p-value=0.001, indicating that the results are statistically different, while the small RMSE value (0.045 m) reflects a low average deviation.

4 CONCLUSIONS

The work carried out in this research contrasts two systems developed for the quantification of step length in race walking. The mentioned sport has been the inspiration for this study; however, the scope of the tests conducted for this document has remained within the laboratory. This project has been directed toward the development of a system for monitoring step length in race walking, focusing on training and monitoring based on easily accessible and highly reliable technologies (Mali and Dey, 2020). The results presented in this work were obtained from a single participant; therefore, they are not generalizable.

Nevertheless, they provide preliminary evidence regarding the behaviour of the systems developed in our laboratory for the future evaluation of stride length.

The instability of the RDU complicates the possibility of establishing effective corrections to minimize errors, whereas the consistency of the SIMPU suggests greater viability for its implementation in step length measurement systems in sports and biomechanical applications. Consequently, the analysis concludes that the use of SIMPU as a measurement system is the less imprecise option in step length measurement, highlighting its potential as a low-cost tool with promising prospects for reducing measurement error, which are fundamental for the development and validation of human movement models.

Based on the results obtained from the absolute error comparison, with -0.01% and 43.77% being the average error for SIMPU and RDU respectively, it is concluded that the power-based measurement method presents problems of readjustment. This is due to the Wi-Fi communication protocol attempting to maintain a stable connection by dynamically adjusting the transmission power. However, this behavior affects the transmission value, making it difficult to obtain consistent measurements.

Additionally, the Wi-Fi protocol parameter of ESP32 is a partially closed system that does not allow the modification in a customized manner to optimize power usage. Consequently, in situations where the distance between devices changes, significant errors in signal transmission are generated, as observed in the obtained results. This demonstrates the limitations of the RDU for accurate measurements in scenarios where connection conditions vary.

Regarding the SIMPU system, the data obtained demonstrates superior performance when using this device for measurements. As a more controlled system, it is easier to make adjustments in the capture of acceleration and position data, thanks to the integration of its accelerometer and gyroscope.

In the second stage of testing between SIMPU and Kinovea, we can statistically observe that the measurements are different (p-value=0.001), indicating a difference in their distribution due to their significant disparity. Based on the recorded measurements, there is a 39% probability that the measurement has an absolute error of less than 5%, a 32% probability that it falls within the range 5% $<$ absolute error $<$ 10%, and a 29% probability that it exceeds 10% (up to approximately 20%, which is the maximum recorded error). Considering a median value of 0.65 m, an absolute error of 5%, 10%, and 20% corresponds to a step length reading error of 3.2 cm, 6.5 cm, and 12 cm, respectively.

While it does not achieve the precision necessary to conform to the metrics established in the measurement of step length in race walking, its results are significantly better than those obtained with the RDU system. The maximum error recorded is approximately 25%, positioning it as the better option among the two systems evaluated. As future work, it is proposed to develop an embedded system with the SIMPU system and conduct field tests with athletes.

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