An Alternative Athlete Monitoring System Using Cost-Effective Inertial Sensing Instrumentation

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Abstract
An examination of the human gait is feasible using inertial sensing. The embedded accelerometer and gyroscope in an inertial measurement unit can evaluate physical activity-based sports and this unit is relatively affordable compared to global positioning systems or video recording quantification. This study developed a cost-effective sports monitoring investigation method with an inertial sensor attached to the right leg of the athletes. In total, four parameters were simultaneously tracked to assess the entire sensor performance in real-time. The accelerometer measured the typical leg angle when walking and running, whereas the gyroscope processed the raw data to obtain the stride frequency from the time-domain data. Moreover, a comparison between the accelerometer and gyroscope was presented while simultaneously attaining the signal to convert the time-domain data to frequency results. Also, the number of strides and linear velocity was expressed as results in this study. To confirm the results, a statistical hypothesis test was implemented for all obtained results. The results indicated that the inertial sensing instrumentation used in this study is promising and could be an affordable alternative option for a sports monitoring system.

Keywords Inertial measurement unit · Sports monitoring · Accelerometer · Gyroscope

1 Introduction
Nowadays, human physical activity can be measured by several sensors, including accelerometers, gyroscopes, global positioning systems (GPSs), cameras, and inertial sensing instrumentation [1–7]. An accelerometer can examine the tilt angle [8] and convert it to the angular velocity. A report on using accelerometers for sports monitoring was presented in 2010 [9]. They investigated the speed related to the foot-step frequency when monitoring professional football league athletes. Furthermore, an accelerometer can be employed to measure the body function of older patients in the hospital to avoid functional ability losses during hospitalization due to minimum physical activity [10]. With the assistance of a wireless communication system, the combination of an accelerometer and surface electromyography (sEMG) can be used to show the level of fitness and healthcare [11, 12]. Additionally, during the coronavirus disease 2019 (COVID-19) pandemic, a research group conducted a study using a cardiopulmonary monitoring system to assist in the diagnosis of athletes, workers, and COVID-19 patients [13]. Their study showed that an accelerometer was implemented along with heart rate and temperature sensors to monitor the recovery of COVID-19 patients. In this case, the accelerometer was operated as an inertial measurement unit (IMU) to determine the motion characteristics of the patients.

Besides the accelerometer, a gyroscope is considered a reasonable alternative to analyze body motion or movement,
because it can produce linear acceleration [14] and at a comparable cost. In contrast, a GPS is still reliable for representing human activity in various geographic spaces by tracking the location [15, 16]. These three sensors are widely used for human physical activity measurement and to quantify the activity to aid in being more effective in the future, particularly for athletes, patients, and rehabilitation engineering systems. With the support device attached to the human body, it is advantageous for the coaches, trainers, therapists, and doctors to identify the necessity of the athletes or patients, hence future activities can be more efficient. Another transducer was also introduced to obtain the effectiveness of human activity in acquiring a decent level of fitness, such as an optical sensor applying a video-motion-based approach [17]. Verification using calibration and marker-less video sensor-based technology could recognize human gait abnormalities by acquiring the normal condition of running as a parameter. The anomalous alternation of this parameter could be considered a gait abnormality.

To quantify human activity, a comfortable, low-cost, and accurate sensor is necessary. Therefore, developing a simple wearable-sensor measurement system from a complex system is essential to obtain a precise assessment of human activity. An appropriate wearable sensor is capable of demonstrating the physiological and biochemical profiles of athletes during training and recovery [18]. A set of apparatus, incorporating a smartphone [19], wearable sensor, and the Internet-of-Things (IoT) [20] with the classifier algorithm is sufficient to collect the data to recognize the activity and healthcare necessity [21], as well as the athlete workload [22]. This measurement environment is beneficial for an individual, or even for a club that uses the athlete service, to prevent injury, accelerate recovery, and maintain fitness by reaching an understanding of the athlete’s physiological ability related to workload or training. Because of the high demand for sports for people with disabilities, a light, comfortable, and wearable physical-activity sensor is claimed to be a necessity to examine the different mandatory training for each sport in the Paralympic Games [23]. In the Paralympic Games, the sports competitions are based on the category of disability. Because of this condition, one athlete would have different necessities compared to another athlete. Therefore, the quantifying activity sensor would be helpful for the coach or trainer to provide the appropriate exercise for a certain athlete. In addition, because of the fair competitiveness shown in the Paralympic Games, it could also be an objective exercise to escalate the positive mindset of athletes.

To compensate for the simultaneous necessity of the accelerometer and gyroscope, an IMU was introduced to accommodate not only the accelerometer and gyroscope but also a magnetometer; therefore, this IMU has a nine-axis configuration, i.e., three axes for each sensor. These three axes are represented as the x-, y-, and z-axis to present a three-dimensional measurement. Additionally, IMU is widely used for estimating the speed, jump power, and height estimation, as well as the movement activity of dancers [24–29]. In such cases, the IMU plays a central role in human activity recognition (HAR).

As mentioned previously, either an accelerometer, a gyroscope, a GPS, a video recording, or an inertial sensor are broadly employed for investigating human physical activity. However, each study had only one or two basic measurements. In [9], the inspection focused on the stride frequency. Meanwhile, the angle assessment was presented in [10]. In [11], the linear acceleration and rotation angle were inspected. Moreover, the quantification using a GPS and video recording [7, 26] was considered expensive compared to that using an accelerometer, a gyroscope, and an IMU, as well as that commonly completed using more than one sensor. Likewise, a comparison study between IMU and indoor positioning systems (IPSs) had been performed in 2020 by Heishman et al. [30]. Their studies emphasized the IMU implementation for the “Player Load” investigation based on the change acceleration on three axes. Their results showed that IMU had reasonable results compared to IPS. However, their system simply evaluated one parameter fractioned into six sub-parameters related to the acceleration. Also, in the same year, Marković et al. performed the IMU as an alternative for assessment, monitoring, and athlete selection for the volleyball team in regards to rapid hand movement properties [31]. They merely used the accelerometer to obtain the absolute acceleration. Again, in this case, IMU has been employed simply for acceleration citation.

Considering the desired measured parameters, cost-effectiveness, and main objectives, as well as offering an affordable apparatus by providing comprehensive measurement of basic physical activity, our study has a four-fold contribution. First, we employed an embedded accelerometer and gyroscope in a single IMU with a six-axis configuration to detect the following four parameters simultaneously in real-time: the typical leg angle when walking and running, stride frequency, number of strides, and linear velocity. To the best of our knowledge, the measurements of these four objective parameters with a single inertial sensor simultaneously in real-time and the assessment of the leg angle using inertial sensing are described for the first time in this research. Therefore, with these four objective parameters, a comprehensive study of measuring physical activity using inertial sensing has been established. Second, we merely implemented a simple electronic configuration to quantify those four parameters to focus on the cost-effectiveness without reducing the measure’s ability. Third, since the IMU was well-calibrated, a straightforward mathematical expression was implemented to obtain those four parameters. In other words, unsophisticated equations were performed
with well-known mathematical representations. Fourth, our results of four parameters provided \( p \) value 0.97 to 0.99 indicating that there were no significant differences between the observed results and expected values, thus our simple system can offer measurement adequately.

The remainder of this paper is organized as follows. Section 2 provides previous related works, while Sect. 3 describes the materials and methods including the apparatus design, objective parameters, and limitations. Subsequently, the experimental results of the physical activity analysis instrumentation are presented in Sect. 4, along with the discussions of the results. Finally, several remarks and conclusions of the study are stated in Sect. 5.

2 Related Works

Over the past several years, HAR had been proposed using IMU to quantify the activity in sports related to basic physical activity assessment. This section reviewed several related studies to easily identify the novelty and contribution of this study. Table 1 presents the summary of published articles and the comparisons with our scheme.

Estimating the hip acceleration and trunk posture relative to the tilt angle have been conducted by Baghdadi et al. in 2018 [32]. They assessed the hip acceleration and trunk angle with a single IMU placed on the right ankle, right side of the hip, and middle of the trunk for each. The IMU was mounted on the ankle assigned as the measurement sensor, then compared with two other IMUs placed on the hip and trunk served as the ground truth for method evaluation. Also, they employed an extended Kalman filter (EKF) and unscented Kalman filter (UKF) to perform their measurement scheme. Their results offered the superiority of EKF compared to UKF by providing the relative and absolute errors. The relative error and absolute error of the hip acceleration using EKF were 6.5% ± 1.42% and 0.96 ± 0.09 m/s², respectively, while applying UKF was 13.02% ± 2.19% and 1.99 ± 0.46 m/s², respectively. Moreover, trunk posture relative and absolute errors utilizing EKF were 3.12% ± 0.56% and 0.68 ± 0.11°, whilst using UKF was 5.3% ± 0.82% and 1.16 ± 0.17°. Their results indicated that IMU along with an optimized algorithm to measure the human gait related to hip acceleration and trunk angle was feasible. However, their findings were limited to the acceleration and angle measurement in the walking task. Another study was performed to quantify the vertical and horizontal distance of two-handed lifting, trunk angle, and lifting duration in 2019 by Barim et al. [33]. They attached five IMUs on the left wrist, right wrist, the upper arm of the dominant hand, upper back, and thigh of the dominant leg. The results from IMU were then

| Study | Aim | IMU Position | Parameter | Result |
|-------|-----|--------------|-----------|--------|
| Baghdadi et al. 2018 [32] | Estimating the hip acceleration and trunk posture while walking | Right ankle, right side of the hip, and middle of the trunk | Hip acceleration and trunk posture | Relative error = 3.12% ± 0.56% to 13.02% ± 2.19%, absolute error = 0.96 ± 0.09 m/s² to 1.99 ± 0.46 m/s² and 0.68 ± 0.11° to 1.16 ± 0.17° |
| Barim et al. 2019 [33] | Measure the vertical and horizontal distance of two-handed lifting, trunk angle, and lifting duration | Left and right wrists, the upper arm of the dominant hand, upper back, and thigh of the dominant leg | Distance of two-handed lifting, trunk angle, and lifting duration | Vertical distance error = 33 cm, horizontal distance error = 6.5 cm, lifting duration error = ~ 1 s, and trunk angle error = ~ 2° |
| Stuart et al. 2019 [34] | Explore the healthy and chronic mild traumatic brain injury participant activity and turning | Waist with the aid of a belt | Bout, step, angle, velocity | \( p \) value < 0.001 to 0.962 |
| Garcia et al. 2021 [35] | Explore a novel quality metric for mild/moderate or severe motor impairment while walking | Waist with the aid of a belt | Angular velocity and frequency | \( p \) value < 0.001 to 0.927 |
| Proposed method | Developed a cost-effective sports monitoring investigation method with an inertial sensor | Right leg | Leg angle, stride frequency, number of strides, and linear velocity | \( p \) value |

IMU Inertial measurement unit
compared with the optical motion capture system as a ground truth. According to the results in terms of vertical distance error 33 cm, horizontal distance error 6.5 cm, lifting duration error $\approx 1$ s, and trunk angle error $\approx 2^\circ$, the distance error had an uncertainty, especially for the vertical distance. Hence, they need improvement corresponding to the distance assessment. In contrast, the angle error had sufficient performance. However, to obtain such measurements, they required five IMUs leading to inefficient evaluation.

The article describing the analysis of free-living mobility corresponding to physical activity and turning using IMU was conducted by Stuart et al. in 2019 [34]. They applied the IMU for quantifying the activity of participants with mild traumatic brain injury (mTBI). They divided the findings into two outcomes, such as macro-level and micro-level outcomes. Additionally, they provided the macro-level physical activity with several sub-measures, for instance, the number of bouts per hour, bout duration, bout duration coefficient of variation, average steps per bout, and total steps per daily bout, while for the micro-level, they offered the number of turn per hour, angle, angle coefficient of variation, peak velocity, peak velocity coefficient of variation, average velocity, average velocity coefficient of variation. Their results showed an adequate performance at the micro-level, while the macro-level outcomes demonstrated $p$ value of more than 0.05. Overall, they had acceptable results. Nevertheless, in terms of step or stride, their results presented a high standard deviation (SD) with the mean SD of 2606 steps for total steps per daily bout indicating inaccurate associations between physical activity and mTBI. The last related work description was the performance of IMU for assessing the gait impairment of post-stroke patients in 2021 by Garcia et al. [35]. They placed a single IMU on the waist to measure the post-stroke patients’ gait smoothness when walking 10 m outdoor. They merely presented the results in the angular velocity and frequency.

To provide an improved and cost-effective instrumentation, we offered a measurement system with a single IMU mounted to the right leg and provided the assessment of the leg angle, stride frequency, number of strides, and linear velocity in real-time, simultaneously. Also, even though we developed our instrumentation with a simple electronic component that related to minimizing the cost, we were capable to present a feasible evaluation of the physical activity by demonstrating a statistical hypothesis test. Likewise, because the assigned IMU was well-calibrated prior to use, uncomplicated mathematical expression can be executed.

3 Materials and Methods

3.1 Apparatus Design

The design introduced in this research was an electronic component connection. A microcontroller and an IMU were the critical components in this study because the microcontroller processed the raw signal data from the IMU to produce the desired objective parameters. The accelerometer obtaining the linear accelerations was used to convert the acquired data into leg angles and stride frequencies. The gyroscope acquired the angular velocities to generate the stride frequencies from the time-domain data. Figure 1 shows the block diagram of the measurement system. The processed data from the microcontroller were sent to a computer with the assistance of two XBee devices that were used for wireless serial communication as a transmitter and receiver. The XBee transmitter was connected to the microcontroller, while the XBee receiver was connected to the computer.

An IMU obtained the raw data to generate the linear accelerations for the accelerometer and angular velocities for the gyroscope. The raw data processed by the microcontroller was then transferred to the computer with the assistance of a wireless communication device (an XBee device in this case). This study used $\pm 6g$ for the accelerometer measurement scale because the measurement could be more than $6g$ if the IMU was close to the ground. A $g$ denotes the acceleration due to gravity, whereas the gyroscope measurement scale was $\pm 1000^\circ/s$ because the pre-processing running measurement was approximately $500^\circ/s$. On the computer, the data were stored as matrices with a sampling time of 0.03 s.

Figure 2 shows the device schematic and pin connections between the IMU, microcontroller, and XBee with a shield. The IMU requires 5 V as the power supply for operation, which can be provided by the microcontroller; hence, the IMU obtains power directly from the microcontroller. The two analog pins are required for the complete operation of the IMU, thus $A_1$ and $A_2$ are connected to the serial data (SDA) and serial clock (SCL) pins, respectively. Moreover, the XBee demands 3.3 V as the power voltage to operate.

![Block diagram of the apparatus](image)

**Fig. 1** Block diagram of the apparatus
which is also supplied by the microcontroller similar to the IMU. The DOut and DIN pins of the XBee are connected to the Rx and Tx pins of the microcontroller, respectively.

To ensure the sensor’s accuracy, the calibration was completed. Calibration aims to adjust the sensor, thus if there is no movement or physical activity, the sensor data reads zero. Since the x-axis is affected by gravity force, prior to being investigated, we did the calibration to convince that the sensor does not produce the linear acceleration and angular velocity when there is no movement or physical activity. Further, the x-axis is unique because even though there is no movement, it always shows 1g due to gravitation force. To overcome this problem, we used a straightforward calibration method by subtracting the x-axis raw data of the accelerometer with 1.

After conducting the calibration, as shown in Fig. 3, the data over the entire axes are zero when there is no physical activity. Because the unit of the gyroscope is °/s, the angular velocity varies with even a small alteration. Nevertheless, this variation was not significant during the calibration, as it showed approximately zero without any physical activity. As mentioned previously, the measurement scales were ±8g and ±1000°/s for the accelerometer and gyroscope, respectively; thus, the raw data should be divided by 4096LSB/g and 32.8LSB/°/s for the accelerometer and gyroscope, respectively, with LSB denoting the least significant bit.

### 3.2 Objective Parameters

The parameters in this study were obtained by mounting the device on the leg of a 22-year-old male with

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**Fig. 2** Pin connections of the IMU, microcontroller, and XBee with a shield

**Fig. 3** Calibration results for the a x-axis, b y-axis, and c z-axis of the gyroscope and d x-axis, e y-axis, and f z-axis of the accelerometer
weight and height = 63 kg and 170 cm, respectively while walking and running on a treadmill. The first objective parameter was the average angle during walking and running. To the best of our knowledge, the measurement of this parameter using inertial sensing is presented for the first time in this study. Hence, this parameter could be obtained with the support of an accelerometer by generating the linear acceleration on the three axes. In addition, the obtained raw data were processed to acquire the leg angle by utilizing the root mean square (RMS). The running performance may be analyzed by quantifying the leg angle. As the existing angle is along the y-axis, the alternating angles can be acquired by

\[ \alpha = \tan^{-1} \frac{a_x}{a_z}, \]  

(1)

where \( \alpha \) is the leg angle and \( a_x \) and \( a_z \) are the linear accelerations along the x- and z-axis of the accelerometer, respectively. A comparison measurement of the leg angle is shown in Fig. 4. This assessment aimed to determine the average angle of the leg at a certain linear velocity. The obtained angles were then compared with the assistance of a video recording. To examine the angle from the video recording, an application called protractor® was employed. The angles 37.7°, 46.7°, and 13.3°, as shown in Fig. 4, represent different stages of a maximum swing; thus, obtaining the average angle involved two strides. With this understanding, the average angle can be expressed as follows:

\[ a_{avg} = \frac{a_1 + a_2 + a_3}{2}, \]  

(2)

where \( a_{avg} \) represents the average angle, \( a_1, a_2, \) and \( a_3 \) are the obtained angles, as shown in Fig. 4a–c, respectively. The sum of the obtained angles was divided by two to obtain the average angle because one cycle required two strides. If the right foot is in front, the angle alternation is positive, and if the right foot is behind, it is negative.

The second objective parameter was the stride frequency. The stride frequency was acquired using a gyroscope. The data from the gyroscope in the time domain were then compared with the fast Fourier transform (FFT) analysis data obtained from the accelerometer and gyroscope itself. The data on the y-axis of the gyroscope was significantly alternating. For better understanding, Fig. 5a depicts the data obtained from the gyroscope for six strides on the treadmill, and Fig. 5b illustrates the demonstration of two strides representing one cycle. The obtained data, as shown in Fig. 5a, produce a certain pattern for each stride. The data between each set of consecutive red dots, red dot 1 to 3, red dot 3 to 5, and red dot 5 to 7, represent two strides each, and every two strides is one cycle. Based on this wave pattern, the analysis of the stride frequency is accomplished using the theory that the foot movement is similar to a pendulum. The pendulum moves in simple harmonics, i.e., moves along the same path.

Figure 5b shows the two strides comprising one cycle with the reference axis information. The graph from red dot 1 to red dot 3 in Fig. 5a is a line chart formed from the gyroscope data on the y-axis triggered by the leg movement shown in Fig. 5b. As shown in Fig. 5a, the data from red dot 1 to green dot 2 represent the first until the third movement shown in Fig. 5b, whereas the third movement to the fourth movement is represented by the data from the green dot 2 to red dot 3, as shown in Fig. 5a. As highlighted previously regarding the angle alternation, a similar condition was applied to determine the stride frequency. If the leg with the attached device swings to the front, the angular velocity changes to a negative value, and if the leg swings back, the angular velocity changes from a negative to a positive value.

The time citation for one full cycle is necessary to acquire the stride frequency from the time domain. As the sampling time was selected to be 30 ms, the frequency can be obtained using the following equation:

\[ \frac{1}{f} = t = \left( x_1 - x_2 \right) \times 0.03, \]  

(3)

where \( f \) is the stride frequency, \( t \) denotes the time, \( \left( x_1 - x_2 \right) \) is the number of samples required to create one cycle of
the pendulum. Figure 6 shows the gyroscope y-axis data for a speed of 1.5 km/h and a walking distance of 50 m. Figure 6a represents the stride data, where a specific pattern of the wave is repeated, indicating that constant walking is performed. Figure 6b shows a part of the sampling data segmentation to show a set of particular data for one cycle of two strides, indicated by the two dashed green lines. The red dots on the left and right indicate the start and finish points of the sampling data for one cycle. With the aid of these data, Eq. (3) can be used to obtain the stride frequency from the time-domain analysis.

Once the analysis from the time domain has been completed, an FFT can be directly applied to simplify the process of acquiring the stride frequency according to the accelerometer z-axis and gyroscope y-axis data. The data from the two sensors show agreement with similar results. The comprehensive stride frequency results utilizing the FFT are presented in Sect. 4. From the frequency of the strides, the number of strides for a particular distance can be calculated as follows:

\[ n = f \times t \times 2, \]  

where \( n \) denotes the number of strides. The stride frequency is for two strides, i.e., the right and left leg swing once; thus, to obtain \( n \), the frequency requires multiplication by two.

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**Fig. 5**  
(a) Gyroscope data of six strides and (b) depiction of two strides with the attached IMU to the leg represented by the green rectangle, as well as the referenced axis information

**Fig. 6**  
Gyroscope y-axis stride data for the speed of 1.5 km/h with a walking distance of 50 m on the treadmill
The obtained data were compared using the video recording to predict the number of strides.

The last objective parameter was the linear velocity. The acquired linear velocity was compared to the treadmill velocity. The linear velocity can be calculated by employing a simple mathematical analysis related to linear motion, as follows:

\[
s_f = \frac{s_t \times t_f}{t_t},
\]

\[
v = \frac{s_f}{t_f},
\]

where \(s_f\) is the distance concerning the stride frequency, \(v\) is the linear velocity, \(s_t\) is the total distance, \(t_f\) is the time for two strides, and \(t_t\) denotes the total time to cover a specified distance by walking or running on the treadmill. To ensure comprehensive results, the calculations of these four parameters were repeated 10 times to regulate the average results. In addition, a standard deviation and statistical hypothesis test were calculated to verify the results.

### 3.3 Limitations

Our study demonstrated decent results to quantify typical leg angle when walking and running, stride frequency, number of strides, and linear velocity in real-time. However, regardless of the obtained results as discussed in Sect. 4, we constrained this study by implementing a simple and affordable single IMU instrumentation. This is reasonable because this study’s ultimate goal is to provide an alternative and cost-effective apparatus to examine athlete performance. In other words, we offer an efficient sports monitoring system by maintaining its capabilities. In addition, XBee was applied as wireless serial communication to collect the data from IMU for then being stored in a computer. According to our experiments, XBee could provide twice the data frequency. In our case, it was 23 Hz. Therefore, the sampling time was selected to be 30 ms = 33 Hz. Using this 33 Hz sampling frequency, Xbue may transfer the data accurately from IMU to a computer. Moreover, we merely attached the apparatus to the right leg for each trial. Because the leg swings are similar to the pendulum, the sensor may generate similar data regardless of the right or left leg. But in this study, we limited the inspection to the right leg. Also, we had a relatively small number of participants directing to limitations for further analysis, for instance, the relationship between occupation or current work with the quantified four parameters. Likewise, energy management was not described, thus there was no information related to the battery capacity per hour. Further, we did not perform the optimum distance between the IMU attached to the participant’s leg (transmitter) and the computer (receiver). Future studies should address these limitations to present reliable results.

### 4 Results and Discussions

This section presents the results and the corresponding discussions related to the study. This study presented 1.5 and 3 km/h as the walking speeds, and 7 and 9 km/h as the running speeds on the treadmill. The first parameter was the leg angle during walking and running, which we discussed systematically. The leg angle was obtained from the data produced by the accelerometer. The angle had a significant alternating effect on the y-axis of the accelerometer; therefore, the linear accelerations along the x-and z-axis were essential data. Subsequently, the obtained raw data were processed using RMS. These RMS data were the typical or effective angles during walking and running. When the collected RMS results, such as the typical angle, were acquired, a comparison to certify the angle results by employing Eq. (2) and the aid of protractor® was conducted, as shown in Fig. 4. Finally, the \(p\) value was applied to measure the angle quantification in a statistical hypothesis test to verify the results.

Another objective was to assess the stride frequency using two methods, namely, the time-domain analysis according to the data produced by the gyroscope and FFT based on the data generated from the accelerometer and gyroscope simultaneously. The male volunteer walked or ran on the treadmill, whereas the data from the IMU were transferred wirelessly to the computer using XBees devices. For the speeds of 1.5 and 3 km/h, the distance walked was 50 m, whereas for 7 and 9 km/h, the distance run was 100 m on the treadmill. The stride frequencies were then calculated from the time-domain analysis and subsequently compared with the FFT results by applying a statistical hypothesis test.

The number of strides was calculated using Eq. (4). To support this research, every test was recorded to obtain the leg angle and number of strides. The number of strides was counted from the first step until the final step for all the speeds. In addition, comparisons were made between the number of strides calculated with Eq. (4) and the video recording. The last objective parameter was the linear velocity. This parameter was determined by employing Eq. (5) and then the results were compared to the treadmill velocity.

Figure 7a illustrates the typical average angle of 10 measurements compared to the angle obtained from the video recording, whereas Fig. 7b depicts the FFT stride frequency with the average of 10 trials compared to the results of the time-domain analysis. Figure 7c illustrates the average number of strides of 10 measurements and the number of strides obtained from the video recording, and Fig. 7d shows the
average linear velocity of 10 trials compared with the treadmill velocity.

To assess the measurement for each objective parameter, a $p$ value was applied from the $t$ test. A $t$ test is an inferential statistical test to determine the difference between the means of two groups of data with these two groups of data not being correlated to each other. The first group was the average results for each parameter (the observed results), whereas the second group was the real values (the expected data). To implement the $p$ value, a significant level ($\alpha$) and degree of freedom (DOF) are required. The employed $\alpha$ was 0.05 as a common standard for conducting a statistical comparison, and the DOF was 3 because the number of objective parameters was 4. After obtaining the $p$ values for each inspection, they were compared with the $\alpha$. If the $p$ value was greater than $\alpha$, the null hypothesis ($H_0$) was accepted, and vice versa. If the $p$ value > $\alpha$, that means there were no significant differences between the observed results and expected values. In this study, our goal was to obtain a $p$ value > $\alpha$ to clarify that the developed device was able to measure the variations in the leg angle, stride frequency, number of strides, and linear velocity simultaneously in real-time under the experimental setup.

**Fig. 7** Comparison of average results of the observed (collected data from the sensor) with the standard deviation (red line) and expected data. a Leg angle assessment compared with the video recording results, b Stride frequency collected from the accelerometer and gyroscope along with the comparison between the average results and results of the time-domain analysis, c Number of strides assessment compared with the video recording results, and d Linear velocity collected from the accelerometer and gyroscope along with the comparison between the average results and the exact velocity of the treadmill.
Figure 7a–d depict the comparisons between the observed results as an average of 10 trials and the expected objective parameters, as well as the standard deviations (red line). They clearly show that the observed results (blue bar) for the four objective parameters are not significantly different from the exact values (yellow bar). For an accurate comparison, the statistical hypothesis test was applied, which showed that the $p$ value was greater than $\alpha$ for all the objective parameters. Therefore, we can claim that the IMU functioned satisfactorily, and the use of IMU was a promising device for quantifying human physical activity, especially for a sports monitoring system. A brief table (Table 2) is structured to present the average values, standard deviations, and $p$ values of the parameters. The standard deviations as shown in Table 2 were extremely small, and the $H_0$ or null hypothesis was accepted; thus, there were no significant differences between the observed results and expected objective parameters. Therefore, the IMU can accurately and simultaneously measure the variations of the leg angle, stride frequency, number of strides, and linear velocity when walking and running. Additionally, for more advanced research direction in the future, our measurement scheme is necessary to improve the real-time data citation by considering the artificial intelligence (AI) implementation [36–38], to optimize the apparatus size; thus it can be more convenient when mounted on the body, and to apply faster wireless communication with remote monitoring.

### Table 2 Average, standard deviation, and $p$ value for each objective parameter

| Objective parameter | Velocity (km/h) | Average | Standard deviation | $p$ value |
|---------------------|-----------------|---------|--------------------|----------|
| Angle ($^\circ$)    |                 |         |                    |          |
| 1.5                 | 25.02           | ±0.06   |                    | 0.99     |
| 3.0                 | 29.49           | ±0.70   |                    |          |
| 7.0                 | 50.99           | ±0.54   |                    |          |
| 9.0                 | 53.39           | ±0.38   |                    |          |
| Stride frequency (Hz)|                 |         |                    |          |
| 1.5                 | 0.55            | ±0.02   |                    | 0.99     |
| 3.0                 | 0.81            | ±0.01   |                    |          |
| 7.0                 | 1.53            | ±0.02   |                    |          |
| 9.0                 | 1.58            | ±0.02   |                    |          |
| Number of strides   |                 |         |                    |          |
| 1.5                 | 134             | ±3.06   |                    | 0.99     |
| 3.0                 | 99              | ±1.53   |                    |          |
| 7.0                 | 165             | ±2.08   |                    |          |
| 9.0                 | 139             | ±1.53   |                    |          |
| Linear velocity (km/h)|               |         |                    |          |
| 1.5                 | 1.45            | ±0.05   |                    | 0.97     |
| 3.0                 | 2.90            | ±0.11   |                    |          |
| 7.0                 | 6.76            | ±0.35   |                    |          |
| 9.0                 | 8.08            | ±0.40   |                    |          |

### 5 Conclusions

The following four objective parameters with the basic purpose of quantifying human physical activity have been measured simultaneously in real-time: the leg angle, stride frequency, number of strides, and linear velocity. To the best of our knowledge, the measurements of these four objective parameters with a single inertial sensor simultaneously in real-time, as well as the quantification of the leg angle using inertial sensing, are shown for the first time in this research. Multiple trials for each measurement were conducted to inspect the physical activity; the participant walked and ran on the treadmill at specific velocities to measure the performance of the embedded accelerometer and gyroscope in a single IMU. The device was attached to the right leg with a proper design. The selected velocities were 1.5 and 3 km/h to represent walking, and 7 and 9 km/h for running; the track distance on the treadmill for walking was 50 m, and for running, it was 100 m. The leg angle results were generated by the accelerometer concerning the alternating angle on the y-axis; thus, the angle may be obtained with the assistance of linear accelerations along the x-and z-axis, and the obtained data were processed using an RMS. The time-domain stride frequency was acquired by utilizing the gyroscope. Subsequently, to confirm the stride frequency, the accelerometer and gyroscope were employed to accomplish the FFT of the stride frequency. The number of strides was calculated from the stride frequency. Then, comparisons were prepared with the steps obtained from a video recording. Ultimately, a linear velocity was used as the critical measurement in this study. Comparisons were accomplished between the measurement results and the actual treadmill velocities. To confirm the comprehensive results, a statistical hypothesis test was performed for each inspection. With these four objective parameters, a comprehensive study of inertial sensing to measure physical activity was conducted. $H_0$ or null hypothesis was accepted because the $p$ value was greater than $\alpha$; thus, there were no significant differences between the observed results and expected values. Overall, the results indicated that the developed apparatus using an IMU is promising and an affordable possibility for quantifying physical activity; thus, it can be implemented in a sports monitoring system. For consideration in the future research direction, our approach requires improvement in the terms of real-time data citation, optimizing the apparatus volume size, and applying faster wireless communication with remote monitoring.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interest to disclose.

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