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Accurate Step-Counting Algorithm using Mobile Sensor

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ABSTRACT:

This research aims to develop a precise and robust algorithm for counting steps in indoor environments using a smartphone's accelerometer. Various daily activities, including standard walking with different smartphone postures and running, were considered in the experimental scenarios. Accuracy in the detection process is achieved through a suitable segregation strategy and predetermined thresholds for each trial. To prevent miscounting, the system generates a new envelope signal that aligns with the actual steps signal while excluding vibrations and noise. The results of this approach were compared to pedometer applications on the Android platform, and the proposed algorithm showed superior detection accuracy compared to other algorithms in the literature. The study focuses on the windowed peak detection algorithm, known for its accuracy and efficiency, making it ideal for mobile devices.

Keywords: indoor positioning, acceleration sensor, gravity sensor, step counting, predictive calculation.

INTRODUCTION

Over the past decade, smartphones have become an integral part of everyday life, serving purposes ranging from communication to surveillance, location, health monitoring, gaming, and behavior detection. These applications rely on built-in communication modules (e.g. Wi-Fi, Bluetooth, GPS) and sensor modules (e.g. accelerometers, gyroscopes, magnetometers) to provide valuable environmental and activity data. As a result, smartphones have gained ground as a development platform in ubiquitous computing, environmental awareness, health management, and other fields, leading to a variety of smart services and applications. Recently, step count data has been widely used for various services, including health management, positioning assistance, and gaming.

Health apps often offer suggestions based on user behavior, while others include step counting games that encourage walking. For tracking and localization, the PDR (walking dead reckoning) function has been introduced, which estimates the user's movement by analyzing signals from inertial sensors in smartphones. Accurate step counting is essential for PDR, a cost-effective and efficient technique often used in conjunction with other location services (e.g. GPS, Wi-Fi Fingerprinting) to enhance performance.

Both gyroscope and accelerometer measurements are closely related to walking, leading to the development of different step counting algorithms. Most research uses accelerometers, which are inexpensive and commonly found in commercial smartphones. However, gyroscopes, while relatively expensive and previously absent from low-end smartphones, provide more accurate motion information by measuring first- and second-order aspects of motion. Therefore, the proposed method relies on gyroscopes.

In this research, a novel phase counting technique based on acceleration and gravity sensors is proposed to improve performance estimation independent of the position of the smartphone and the pedestrian's walking or running movements. The effectiveness of the proposed method is proven by tests and its performance is compared with the performance of standard schemes. According to the results, the performance of the proposed scheme is better compared to the traditional schemes no matter what the pedestrian is walking or running, even when the phone is in different positions such as pants pocket, shirt pocket, and hands.

Since walking generates cyclic signals, our proposed method uses a spike detection algorithm, which is highly effective for identifying walking patterns. This approach increases the accuracy of step counting by analyzing spikes in the signal data. By using the Fast Fourier Transform (FFT) to analyze the spectrum of gyro measurements, we can better detect and count steps, leading to improved performance in a variety of applications.

Therefore, it is worth noting that the proposed scheme is a clear and efficient technique for continuous step counting. The remainder of the paper is organized as follows. Section 2 presents relevant works of traditional step counting methods. Section 3 provides a full explanation of the proposed scheme. In Section 4, the effectiveness of the proposed scheme is evaluated through experiments and compared with the standard method. Finally, the last observations are presented in Section 5.

RELATED WORKS

Several attempts have been made to construct algorithms for counting steps using accelerometer signals. For example, in [6], an algorithm for thresholding the magnitude of accelerometer values based on walking pace was developed. This system achieved an average accuracy of 96.6% across five gait samples that ranged from 16 to 44 steps. However, the data collection methodology was not specified, although the device was placed close to the subject's centre of gravity.

In [7], the authors evaluated a wide range of algorithms for gait detection and step counting. The study explored various techniques, including simple time-domain thresholding, frequency-domain analysis, nonlinear template matching, and machine learning. The authors compared nine methods: window peak detection, mean number of crossings, normalized autocorrelation, dynamic time warping, short-time Fourier transform, continuous wavelet transform, discrete wavelet transform, hidden Markov model, and k-means clustering. The study collected 130 recordings of data from 27 participants who held their smartphones in four different positions: in hand, front pocket, back pocket, and purse. The video recording of each session served as a reference. The authors found that window peak detection, hidden Markov model, and continuous wavelet transform performed best under all circumstances, with a mean error of approximately 1.3%. The windowed peak detection algorithm was particularly noted for its efficiency due to its lower computational complexity compared to other methods.

Gu et al. [8] proposed a robust peak detection system designed to handle false alarms. This approach added constraints on peak detection such as periodicity (time difference between adjacent peaks), similarity (peak distance between two acceleration windows), and continuity (number of acceleration readings deviating above threshold). These features help prevent "false walking" that occurs when users perform activities such as texting, calling, watching videos or playing games while standing still. In their study, eight volunteers were asked to walk 300 steps with a smartphone in two different states: (a) a fixed position of the phone and (b) an arbitrary position of the phone. The system showed an average error of 3.54% for walking and 14.04% for fake walking scenarios.

While these articles provided valuable insights, they did not provide the source code for their algorithms or the datasets used for validation.

Various approaches have been developed to count steps using accelerometer data:

1. ***Thresholding Approach:*** This method counts steps by determining whether the sensory input meets predefined threshold values, which may vary depending on the location of the device and the location of the user. For example, in [15] different states (e.g. not walking, possibly starting a step, standing still) and corresponding thresholds were used to calculate steps. Another study [12] attached a sensor to the user's ankle that increased the number of steps when the acceleration exceeded a certain threshold. Despite its simplicity, finding a universal border that works in different smartphone scenarios and positions can be challenging.

2. ***peak detection approach:*** Steps are estimated based on the number of spikes in a sequence of sensory inputs without using predefined thresholds. However, this method can suffer from spurious spikes caused by external noise and disturbances. In [16], low-pass filtering was used to eliminate interference, while another study [17] shortened the time interval between peaks to minimize misjudgement. Another approach [18] used two filters to reduce acceleration jitter.

3. ***Zero-counting approach:*** This method counts steps by identifying the number of zero points in the sensory data, which is prone to distortion and usually requires pre-filtering and smoothing of the original data. For example, [14] used a 6th-order Butterworth filter to reduce noise and a timeout mechanism to remove unnecessary zeros. Although this algorithm achieved an accuracy of over 96%, it required the smartphone to be placed vertically in a pants pocket. Both spike detection and zero crossing rely on acceleration or angular velocity to detect gait cycles. While effective for vertical acceleration, they are less accurate when the smartphone is not securely attached to the user's body.

4. ***Autocorrelation Methodology**:* This technique finds cyclical periods directly in the time domain using autocorrelation analysis. It can achieve good performance at a reasonable cost compared to frequency domain methods. In [17], the adaptivity of this approach was enhanced by dynamically adjusting the sliding distance. Studies [23, 24] evaluated the horizontal and vertical components of acceleration and angular velocities, which yielded good detection accuracy, but yielded high computational costs for the transformation of the reference systems.

Step counting can be performed using a variety of tools, including cameras [5], accelerometers [6]-[8], and commercial pedometers [9]. This paper focuses on step counting methods using smartphone accelerometers, including thresholding [10], peak detection [12], correlation analysis [4], and spectral analysis [14]. Threshold-based approaches assess whether the accelerometer data meets specific conditions using methods such as simple thresholding and zero velocity update (ZUPT). However, determining a uniform threshold suitable for different smartphone and user positions is difficult.

Peak detection-based methods count steps by identifying peaks in accelerometer readings, avoiding the need for thresholds. These methods typically extract local peaks in the acceleration amplitude and impose a temporal constraint to reduce overcalculation. Despite their effectiveness, these methods may not be accurate for step mode transitions or smartphone positions.

Correlation analysis methods calculate steps by comparing correlation coefficients between adjacent windows of accelerometer data. These methods convert acceleration data from the time domain to the frequency domain using techniques such as discrete Fourier transform, dynamic time warping, or autocorrelation. Although accurate, these methods are computationally expensive and less suitable for smartphone applications.

In conclusion, the peak detection approach, which counts steps by identifying peaks in accelerometer readings, remains one of the most efficient and accurate step counting methods, especially when combined with time constraints to minimize errors during transitions. This method, along with others such as autocorrelation and zero-crossing, makes a significant contribution to the development of reliable and versatile step counting algorithms suitable for various smartphone applications.

METHODOLOGY

In this work, we utilize the smartphone's accelerometer to gather acceleration data during human movement. The data is then transferred to MATLAB Drive using an application installed on the users' smartphones, called "MATLAB on Mobile." This application provides access to the sensors available on the user's smartphone. The accelerometer data obtained includes four key parameters:

1. Timestamp Values: These indicate the date and time in hours, minutes, and seconds.
2. X-axis Acceleration: This represents the acceleration values along the X-axis.
3. Y-axis Acceleration: This represents the acceleration values along the Y-axis.
4. Z-axis Acceleration: This represents the acceleration values along the Z-axis.

Most accelerometer modules measure acceleration as a vector and can detect both linear and angular acceleration. Angular acceleration is defined as the rate of change in angular velocity over time, while linear acceleration is the rate of change in linear velocity over time. In this study, we focus solely on the linear acceleration vector to estimate the number of steps taken. The angular acceleration resulting from human steps is minimal and can be ignored.

By concentrating on linear acceleration, we can effectively estimate step counts, ensuring our approach is both accurate and efficient.

Acceleration (a):

$$a = \lim_{\Delta t \to 0} \frac{\Delta v}{\Delta t} = \frac{dv}{dt}$$

Where a denotes acceleration in meters per second squared (m /s²), Δv represents the change in velocity in meters per second (m/s), and Δt represents the time interval in seconds. The accelerometer measures linear acceleration separately along the x-axis, y-axis, and z-axis. Predicting the accelerometer's orientation every time the step counting feature is activated is challenging. Therefore, the acceleration vector is converted into a single scalar value at each time point. This ensures that acceleration values are accurately determined for human walking or running, regardless of the accelerometer's orientation. The total acceleration value is calculated by taking the square root of the sum of the squares of the three acceleration components, as described in the following equation:

Overall Acceleration Value:

$$a_{all} = \sqrt{a_x^2 + a_y^2 + a_z^2}$$

The gravitational force impacts the acceleration value due to the architecture of the accelerometer module. Estimating the axis affected by gravity is challenging because it depends on the smartphone's orientation, whether carried by hand or placed in a pocket. Figure 1 illustrates the acceleration signals along the three axes. Consequently, gravitational influence is removed from the overall acceleration signal as follows:

Final Acceleration Signal:

$$a_{final} = a_{all} - \bar{a_{all}}$$

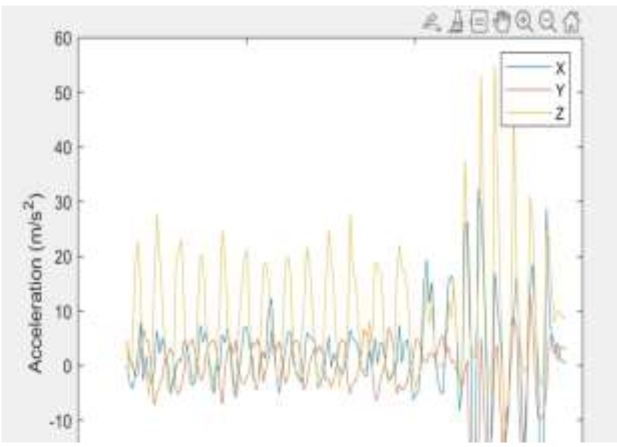

Figure 1: Acceleration values on X, Y, and Z-axis,

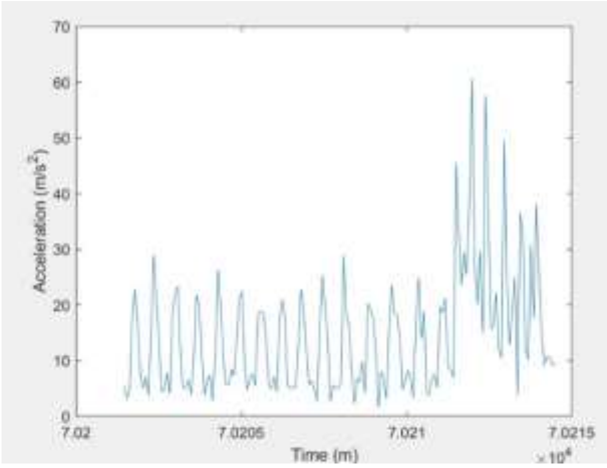

Figure 2: Sum of Acceleration Vectors of X, Y, and Z-axis after subtracting the mean value

Human steps produce small peaks in the acceleration data, which can vary depending on walking behavior, as shown in Figure 2. Electromagnetic interference from surrounding appliances can also introduce noise into the signal. To estimate the number of steps accurately, it is necessary to identify the maximum local peaks that exceed a specifically tuned threshold.

This can be achieved by generating an envelope function in MATLAB using spline interpolation over local maxima separated by at least a certain number of samples (n_p). The value of n_p can be calculated using MATLAB. This method effectively removes unwanted vibrations and false steps, making step counting more accurate, as depicted in Figure 3.

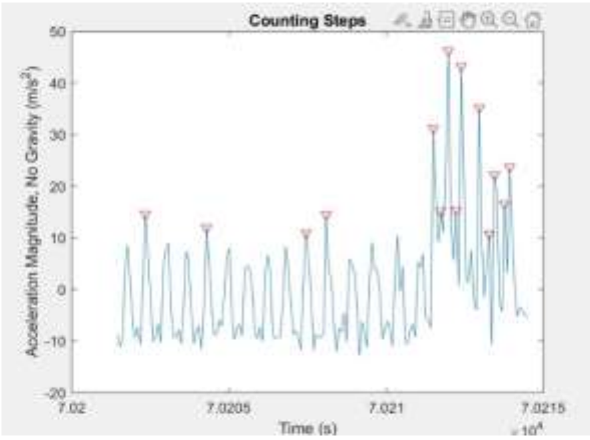

Figure 3: Using the envelope function for measurement will eliminate noise and eliminate vibration.

In this approach, the primary factor influencing the accuracy of step estimation is the threshold definition. This threshold depends on the scale value, the step value, and the average value of the quadratic acceleration function envelope. Therefore, the threshold is defined by equation 4 which ensures that the threshold is appropriately adjusted based on the relevant parameters, enhancing the accuracy of the step-counting algorithm.

Threshold Definition:

$$\epsilon = \frac{avg(a_i) + avg(a_j) + avg(a_k)}{n_p} - a_d, \{a_d \in (3,5)\}$$

where a_x, a_y, a_z represent the upper peaks envelope, d is a correction factor, np is the number of samples, and it is defined as follows:

$$n_p = \text{round}(\frac{R_s}{S_r})$$

In this work, the step rate S_r is assumed to be five steps per second, representing the average human step rate. The sampling period τ_s is calculated using the timestamps of the new signal data by finding the difference between consecutive values in seconds. The segregation approach involves generating a new signal based on the envelope function, which provides the upper limit for the average of the measured acceleration signals. This process removes the impact of vibrations and noise, facilitating accurate step counting, as shown in Figure 3 in red. This transformation ensures precise step detection. The next step is to find the maximum difference value to represent the sampling period, as given by the following equation:

$$\tau_s = \max(t_{n+1} - t_n)$$

After that the sample price is calculated as follows::

$$R_s = \frac{1}{\tau_s}$$

Comparing the peaks of the final acceleration signal, P_{isk} (), derived from the envelope function with the threshold ε allows for estimating the number of steps over the path length. Mathematically, the constraint necessary for counting the number of peaks exceeding the calculated threshold can be expressed as follows:

$$a_{\text{final}} > \varepsilon$$

Table 1 shows the steps and procedures of the step calculation algorithm.

Table 1: Proposed Algorithm steps

Proposed	**Algorithm Steps**
1.	Collect a_x, a_y, a_z
2.	Calculate a_{all} and a_{final}
3.	Define step rate S_r=5
4.	Calculate the sampling period τ_s , and it is defined as max ($t_{n+1} - t_n$) for n=0,1,2…,k where k is the number of samples.
5.	Calculate the sampling rate as $R_s=1/\tau_s$
6.	Calculate n_p = round(R_s/S_r)
7.	Apply envelope function on a_{final} a_x, a_y, a_z to return the upper peaks envelope a^*_{Final} a_x, a_y, a_z.
8.	Define the threshold as follows: $$\epsilon = \frac{avg(a_i) + avg(a_j) + avg(a_k)}{n_p} - a_d, \{a_d \in (3,5)\}$$
9.	Count the peaks P_{sk} (i) for $a^*_{final} > \varepsilon$
10.	Display the step count if finished

EVALUATION AND RESULT

Experiments were conducted at a private institution with numerous electronic devices emitting electromagnetic noise, which interfered with the measured data. The Poco M4 5G accelerometer was used for data collection. Four different scenarios, summarized in Table 2, were considered. Figure 4 shows the smartphone's position during the experiments.

Table 2: Reporting of activities in empirical context.

Symbol	**Activity**
A	Walking at varying speeds with the smartphone is carried by the hand
B	Walking at varying speeds with the smartphone is placed in the Jacket pocket
C	Walking at varying speeds with the smartphone is placed in the trousers' front pocket
D	Running at varying speeds with the smartphone is carried by the hand

Figure 4: Position of the smartphone in the experiment

Steps Counting During Different Daily Activities:

This section examines the accuracy of the proposed step-counting algorithm during various daily activities. The accuracy of step detection is defined as follows:

$$\text{Accuracy} = [1 - (\frac{S_e - S_a}{S_a})] \times 100\%$$

Here, Se represents the estimated number of steps, and Sa is the actual number of steps. Ten experiments with varying speeds and path lengths were conducted for each case study, as detailed in Table 3. The algorithm achieved an average accuracy of over 99% for normal walking when the smartphone was carried in the participant's hand, with a miscount of only one or two steps regardless of the path length. In the next scenario, where the smartphone was placed horizontally in the participant's jacket pocket, the average accuracy was about 98%. The third scenario involved placing the smartphone in the front pocket of the participant's trousers.

The results showed that the average accuracy dropped to 96.7% due to the smartphone's location. For the running task, when participants held the mobile phone in their hands, the average accuracy of the cases was 96.9%, with a loss of 1% compared to the walking model. Figure 5 shows the average accuracy for the experimental conditions. Figure 6 shows the detected and actual steps for each scenario. In Figure 6(a), 19 steps were detected, which is 1 step less than the actual number in scenario A, probably due to the calculation error caused by the initialization. Figure 6(b) shows that the algorithm can identify the exact number of steps with zero error.

Test Scenarios					
Exp. No.	**Actual Steps**	**A**	**B**	**C**	**D**
1	10	10	11	9	11
2	20	19	20	21	21
3	30	29	30	29	29
4	40	40	51	39	40
5	50	50	51	51	51
6	60	60	59	60	61
7	70	70	70	73	72
8	80	80	82	80	81
9	90	91	89	92	92
10	100	100	100	98	102

Table 3: Comparison of the actual number of steps and the number of detected steps in different conditions according to the proposed method.

Placing the smartphone in the trouser pocket may cause unwanted vibrations, leading to an overcount of steps, as shown in Figure 6(c). In the running scenario, errors might occur during transitions from movement to stillness, resulting in an increased number of detected steps, as illustrated in Figure 6(d).

Comparison with other Pedometers:

This section evaluates the accuracy of the proposed algorithm compared to other pedometers. Two Android applications were used to detect the number of steps during normal walking and running activities, alongside a REDMI BAND PRO for validation. The first application was Pedometer by Xiaomi Mi Band 2.0 Inc., and the second was Pedometer for Walking, both available on the Google Play Store. Tests were conducted under identical conditions to ensure a valid comparison. The results demonstrated that the proposed algorithm improved detection accuracy by at least 3% compared to the other methods.

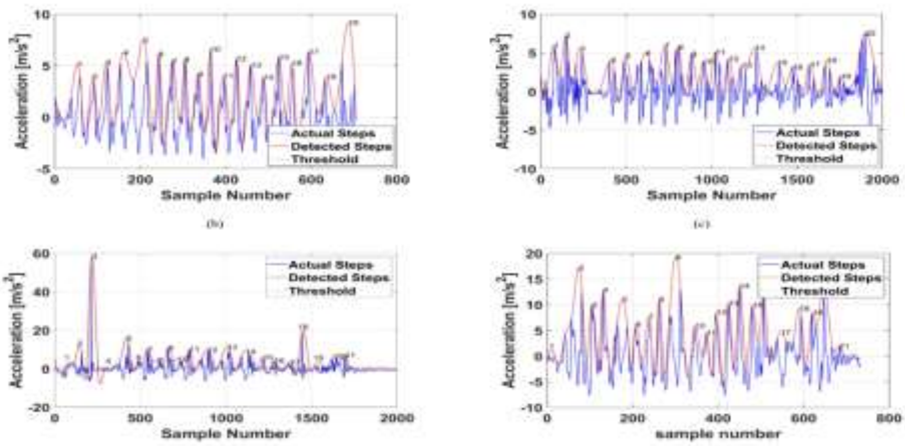

Figure 3: Steps to find different Scenarios. (a) Walk normally and hold the smartphone (b) walk normally, put the smartphone in the right pocket of your shirt; smartphone while operating mobile phone

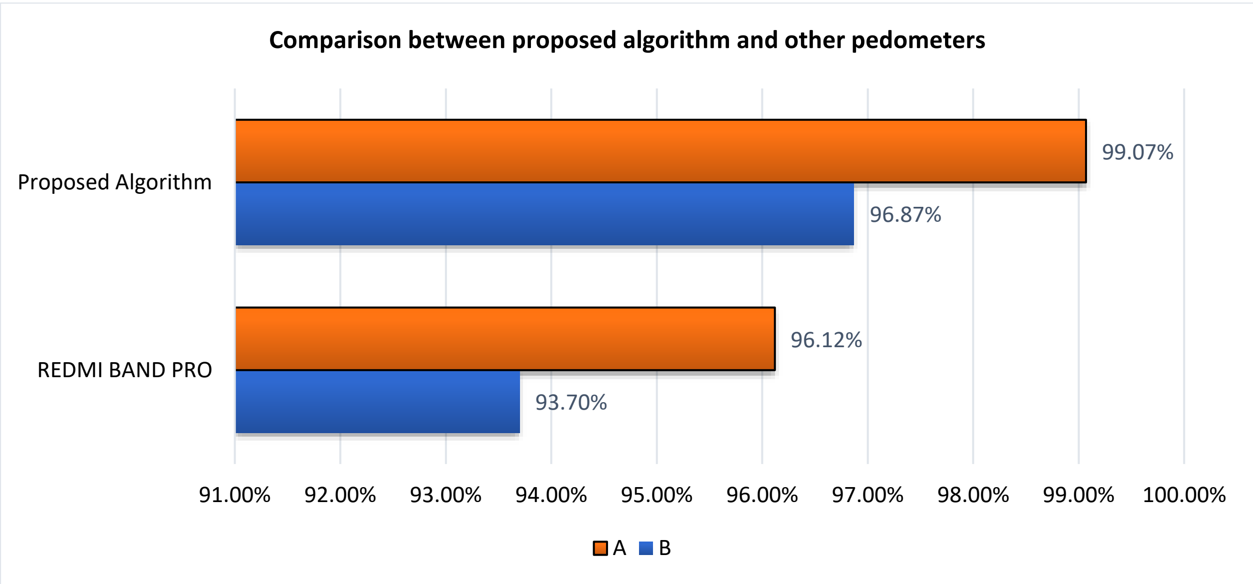

Figure 4: The average accuracy of the proposed algorithm compared to REDMI BAND PRO

The average accuracy of Redmi Band PRO is 96.12% for walking and 93.73% for running, which ranks second in performance. It is worth noting that Redmi BAND PRO, unlike other applications, does not use a mobile accelerometer. The results of the study are shown in Figure 6.

CONCLUSION

This study introduced and validated a robust step detection algorithm using smartphone accelerometer data. By generating a new signal based on the envelope function, the algorithm effectively mitigates vibrations and noise, ensuring accurate step counts. Tested under normal walking and running scenarios with the smartphone in various positions, the algorithm achieved over 97% accuracy across all cases.

Accuracy varied with smartphone placement: it dropped to 96.7% when in the trouser pocket due to vibrations and slightly reduced to 96.9% when held in hand during running. These results demonstrate the algorithm's robustness and adaptability to different user behaviors and phone positions.

The algorithm outperformed two Android applications and the REDMI BAND PRO by at least 3% in step detection accuracy. The REDMI BAND PRO, which does not use the smartphone accelerometer, showed an average accuracy of 96.12% for walking and 93.73% for running, highlighting the algorithm's superior performance.

The study indicates that the proposed algorithm is suitable for both online and offline step counting, with a step rate of up to 5 steps per second and a sampling rate between 50 Hz and 100 Hz. Its accuracy and efficiency make it ideal for various smartphone applications, providing a reliable solution for diverse step-counting scenarios. Future research may focus on refining the algorithm and applying it to more complex environments.

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