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Peak-Valley Detection and Step Counting Method Based on Kalman Filter on Android Smartphones

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ABSTRACT

With the popularity of smartphones and the application of built-in sensors, it makes easier for users to obtain daily walking steps information as an important indicator of health evaluation. However, The complexity of the environment and different user's walking speed will lead to a decrease in the accuracy of the step counting. The commonly used algorithms such as the basic peak-valley detection and the dynamic threshold method cannot directly process the noise-containing source signal of the smartphone sensor, so that it cannot be accurately record the user's daily steps. In this paper, We propose a Kalman filter algorithm for feature extraction of raw data, which greatly reduces the influence of the pseudo-peak in the noise signal. And we sets moving average as threshold for step detection, at the same time, sets the different peaks time threshold to remove the number of invalid steps. The experimental results based on MATLAB simulation platform show that the improved algorithm has high robustness under various walking cases which basically meets the users' actual needs. The Android mobile App was designed to verify real-time performance based on basic peak-to-valley detection algorithm.

1. Introduction

People use smartphones very widely in modern life and smartphones contain many sensors, such as accelerometers, GPS, gyroscopes and so on. It is very common to develop enterprise applications for smartphones. However, the sensors in smartphones are usually cheap and have poor performance, and that causes the sensor signal analysis methods widely used in other systems are often no longer applied. It is necessary to carry out in-depth development and research on mobile phone sensors, and explore sensor information processing methods suitable for smart phones in order to obtain better applicability.

The number of steps calculated using the sensor data of the mobile phone can enable the mobile phone user to more quickly understand their own movements and provide motion suggestions and decisions for the mobile phone user. For example, the acceleration sensor in the smart phone can measure the real-time acceleration of the mobile phone user during the movement, and the GPS can obtain the current geographical location information of the user, so the sensor system composed of various sensors can give the user the motion situation in all directions. Besides, inertial sensors can capture small movements and have been widely used in many systems [1]. However, the accuracy of the relevant sensors in these smart phones is not high enough, so it is necessary to design a reasonable step processing algorithm suitable for the characteristics of the sensors, thereby improving the mobile user experience and product satisfaction.

From the perspective of sensor information processing, most researchers judge and record the number of steps of the mobile phone user according to the influence of the mobile user's motion state on the sensor data. The most common study is to follow the synthetic acceleration of a mobile phone user while exercising.

Whenever the mobile phone user moves a complete motion state, the synthetic acceleration data presents an approximate sinusoidal signal of a peak and a trough. To detect peaks and troughs, the researchers used the peak-to-valley detection algorithm to calculate the number of steps. When the noise generated during motion is too large, the dynamic threshold method can be used to capture the correct peaks from the data with false peaks and count them. According to the above ideas, these algorithms are generated： peak-valley detection algorithms [2,3], handheld devices will bring low-amplitude and fast-twitching states, which will cause interference in peak detection. Self-adaptive step counting algorithms [4-6], the pedestrian motion state is divided into normal state and abnormal state. According to the intrinsic correlation

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between the maximum global acceleration of each step and the motion state, the experiential thresholds of different states are obtained. There is also a problem that it is impossible to eliminate the interference caused by the pseudo-peaks in the sensor itself. Step counting algorithms based on SVM [7] are relatively mature, this algorithm has a large amount of computation, and it is not easy for mobile phone users to verify its real-time performance.

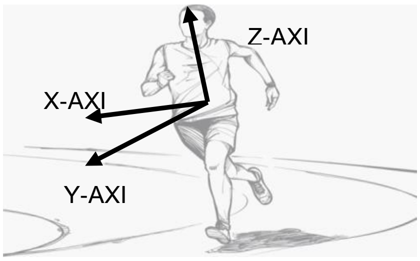


Fig. 1. The human body produces acceleration in three directions while exercising. And it can be acquired by the accelerometer from the smartphone.

Besides there is currently no detailed understanding of how well pedometer works when applied to smartphones in typical, unconstrained use [8].

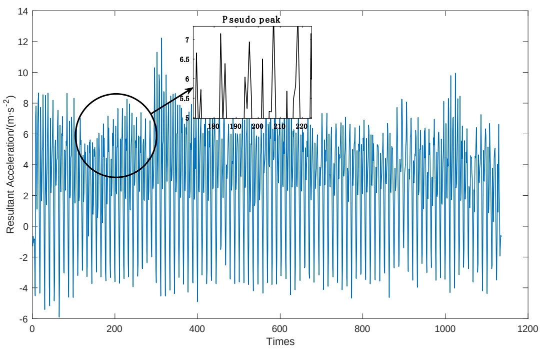


Fig. 2. The pseudo peak in the resultant acceleration

Some researchers have used the moving average method to filter the source signal, and obtained good simulation results. Furthermore, in real life, users often generate multiple walking states, which cause the human body acceleration signal collected by the smartphone itself to be a long-cycle and unstable signal.

At the same time, the noise caused by the accuracy of the sensor also produces more interference. Three degrees of freedom can be used to determine the attitude of an object in a moving space [9]. When the man is walking, the periodic accelerations in the three directions of the center of gravity are the lateral X-axis, the forward Y-axis, and the vertical Z-axis, which are shown in the Figure 1. Three-axis information fusion can effectively reduce the error [10].

It is usually necessary to place different positions on the human body according to the type of sensor to collect a more stable acceleration signal. Different acceleration signals will be collected for the user to hold the smartphone in the hand and in the pocket. Regardless of where the sensor is placed in the body, there is at least one active axis. The active axis produces a sinusoidal acceleration data. A gait cycle signal is similar to a periodic sinusoidal signal.

In the process of counting the number of steps, the collected accelerometer data contains noise, which will seriously affect the performance of the algorithm. The pseudo peak shown in the Figure 2 is a typically affect factor in the resultant acceleration. Based on this, this paper uses Kalman filter technology to preprocess the noise data, and combines the peak-valley detection algorithm with adaptive threshold to count the actual number of steps from the filtered acceleration data, thus achieving effective step counting on the smartphone.

2. Wave crest step counting method

2.1 Feature extraction

The different location of the smartphone will cause the different active axis of the sensor acceleration. To improve the robustness of the algorithm in practical applications, the three-axis synthetic acceleration is extracted. Assuming that the acquired 3D acceleration data are x_i, y_i and z_i, the unit is g ($1g = 9.8N \cdot m/s^2$) then the combined acceleration a is calculated as follows:

$$a_i = \sqrt{x_i^2 + y_i^2 + z_i^2}, i = 1, 2, \cdots n \tag{1}$$

2.2 Kalman filter

In order to obtain effective acceleration characteristics, this paper uses Kalman filter algorithm to smooth the combined acceleration curve and obtain a smooth approximate sinusoidal signal without pseudo-peak. Kalman filter algorithm is an optimal estimation algorithm [11-13], especially suitable for processing multi-variable, time-varying, non-stationary time series data. It is an iterative feedback process, which can be divided into two parts: time update process and measurement update process. The time update process is the covariance of the estimated value and error obtained by the previous time point, and the state variable of the current time point. Estimating, obtaining the a priori estimate at the time point; the measurement update process combines the a priori estimate with the measured value, improves it to obtain the posterior estimate, obtains the feedback of the time update equation, and updates and estimates according to the cycle.

Assume that the process model and measurement model of a linear discrete system are as follows:

$$x(k+1) = A(k)x(k) + w(k) \tag{2}$$

$$z(k) = C(k)x(k) + v(k) \tag{3}$$

where $x(k)$ is the amount to be estimated and $z(k)$ is the measurement data obtained by the sensor. Then (2) is the system process model, which refers to the law of the state to be estimated in the system as a function of time. $A(k)$ is the process matrix, which represents the relationship of state transitions. $w(k)$ is process noise, $C(k)$ is the measurement matrix, and $v(k)$ is the measurement noise. Let $w(k)$ and $v(k)$ be white noises with zero mean uncorrelated, and the covariance matrix is known, $Q(k)$, $R(k)$respectively, then $w(k) \sim (0, Q(k)), v(k) \sim (0, R(k))$.

Known by (2):

$$\hat{x}(k|k-1) = A(k-1)\hat{x}(k-1|k-1) \tag{4}$$

If the estimated variance of $\hat{x}(k-1|k-1)$ is known

$$P(k-1|k-1) = E[(x(k-1) - \hat{x}(k-1|k-1))(x(k-1) - \hat{x}(k-1|k-1))^T] \tag{5}$$

Then the estimated variance $P(k|k-1)$ of $\hat{x}(k|k-1)$ is defined as

$$P(k|k-1) = E[(x(k) - \hat{x}(k|k-1))(x(k) - \hat{x}(k|k-1))^T] \tag{6}$$

Substituting (2) and (4) into (6) gives:

$$\begin{aligned}P(k\,|\,k-1) &= E[(A(k-1)(x(k-1)-\hat{x}(k-1\,|\,k-1))+w(k-1))\\ &\times(A(k-1)(x(k-1)-\hat{x}(k-1\,|\,k-1))+w(k-1))^T]\end{aligned} \tag{7}$$

Considering that the state is not related to the process noise, it can be obtained from the above formula:

$$\begin{aligned}P(k\,|\,k-1) &= A(k-1)E[(x(k-1)-\hat{x}(k-1\,|\,k-1))(x(k-1)-\hat{x}(k-1\,|\,k-1))^T]\\ &\times A^T(k-1)+E[w(k-1)w^T(k-1)]\end{aligned} \tag{8}$$

Then

$$\begin{aligned}P(k\,|\,k-1) &= A(k-1)P(k-1\,|\,k-1)\\ &\times A^T(k-1)+Q(k-1)\end{aligned} \tag{9}$$

When there is a new measurement data $z(k)$ update, the following update equation is summarized as follows:

$$\hat{x}(k\,|\,k)=\hat{x}(k\,|\,k-1)+K(k)(z(k)-C(k)\hat{x}(k\,|\,k-1)) \tag{10}$$

$$\hat{x}(k\,|\,k-1)=A(k-1)\hat{x}(k-1\,|\,k-1) \tag{11}$$

$$K(k)=P(k\,|\,k-1)C^T(k)(C(k)P(k\,|\,k-1)C^T(k)+R(k))^{-1} \tag{12}$$

$$\begin{aligned}P(k\,|\,k-1) &= A(k-1)P(k-1\,|\,k-1)\\ &\times A^T(k-1)+Q(k-1)\end{aligned} \tag{13}$$

$$P(k\,|\,k)=(I-K(k)C(k))P(k\,|\,k-1) \tag{14}$$

Initialization conditions:

$$\begin{aligned}\hat{x}(0\,|\,0) &= E[x(0)]\\ P(0\,|\,0) &= E[(x(0)-\hat{x}(0\,|\,0))(x(0)-\hat{x}(0\,|\,0))^T]\end{aligned} \tag{15}$$

In this paper, the original 3D acceleration data is used to calculate the combined acceleration, and more information of the original data is retained. The Kalman filtering method is introduced to process the feature data, and more effective features are obtained. The experimental results show that the acceleration characteristic data from the Kalman filter made the robustness of wave crest step counting method be improved greatly.

2.3 Wave detection

The characteristic data of the Kalman filter is a sinusoidal curve. In this paper, the peak data trough threshold detection algorithm is used to detect the peak value based on the sliding average value. The algorithm flow chart is shown in Figure 2. We know that a gait cycle acceleration data contains a peak and a trough, and is recorded as two steps. The moving average value is used as the threshold value, so when the new acceleration data is acquired, it is judged whether it is greater than the threshold value and greater than the previous time value. If the condition is met, the point is in the rising state, and the point is taken as the new wave peak, otherwise the last time value is retained as the wave peak, and if it is less than the threshold and less than the previous time value, the point is a trough. In both cases, the number of steps is added and recorded, and at the same time, the moving average is recalculated. In addition, it is necessary to set an appropriate time threshold according to the frequency of the rate of walking to eliminate the number of invalid steps caused by adjacent too close peaks. Flow chart of peak detection algorithm based on Kalman filter is shown in Figure 3 and Figure 4.The algorithm runs in the following steps. Firstly, read the data and calculate the combined acceleration. Then, the combined acceleration is passed through Kalman filter to get a smooth characteristic curve. Finally, it is judged whether the current value satisfies the experiential peak threshold condition and the time threshold condition. If the conditions are satisfied, then it is judged to be one effective steps.

3. Experimental results and app implementation

3.1 Data set

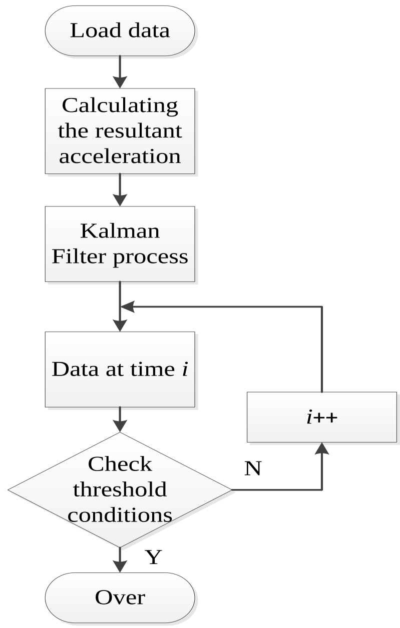


Fig. 3. Flow chart of peak detection algorithm based on Kalman filter

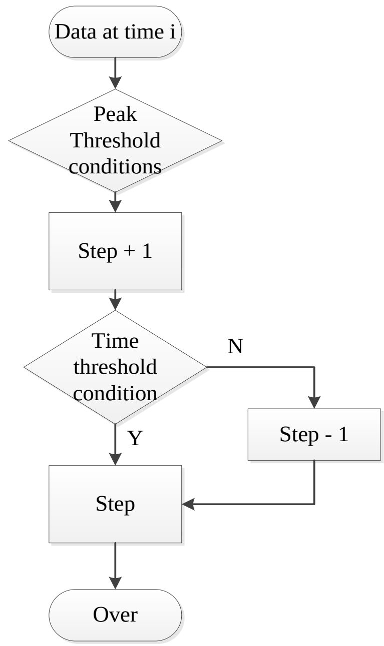


Fig. 4. Flow chart of peak detection algorithm based on Kalman filter.

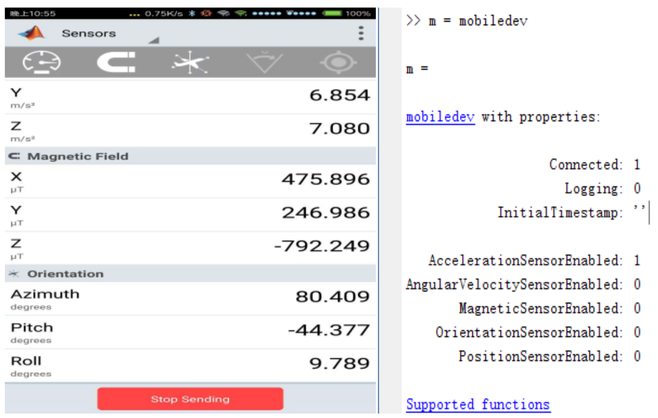
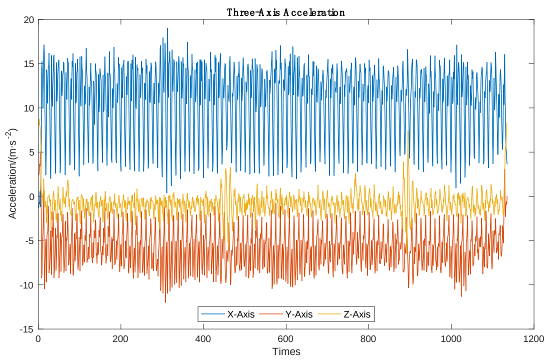


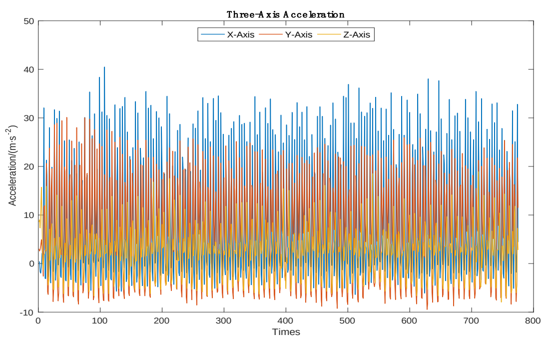
Fig. 5. Android mobile phone data acquisition interface

We can collect the real data of the built-in sensor of smartphone through the smartphone APP MATLAB. Firstly, we use the PC-side

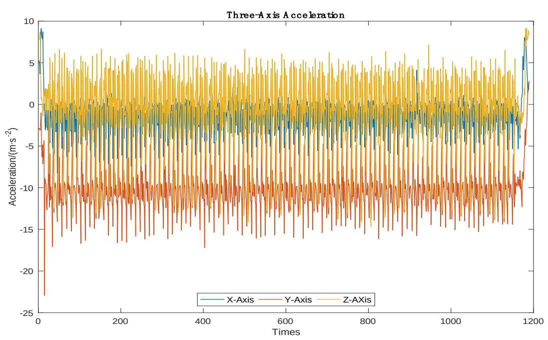
MATLAB to establish a connection with the mobile phone APP MATLAB, then set the acquisition frequency and select the transmission accelerometer signal as shown in Figure5. we can collect and save the accelerometer data and time when the volunteers carry the mobile phone while walking. The state of walking of the human can be roughly divided into normal walking and running according to the walking speed. Under normal walking state, the walking frequency is basically maintained at 2.5 Hz and the running state is 5 Hz. All experimental data in this paper are sampled with 50 frequencies, that means, we collected 20 times in milliseconds. All the data were from the same volunteer and the same Android smartphone and we do three experiments separately. Firstly, the volunteer hold the mobile phone and walked 200 steps. Secondly the volunteer held the mobile phone and ran 200 steps. Finally, the volunteer walked 200 steps with the phone in his right trouser pocket. The real data are shown in Figure 6. The data after the Kalman filter is shown in Figure 7.



(a)Walking in hand 200 steps original data

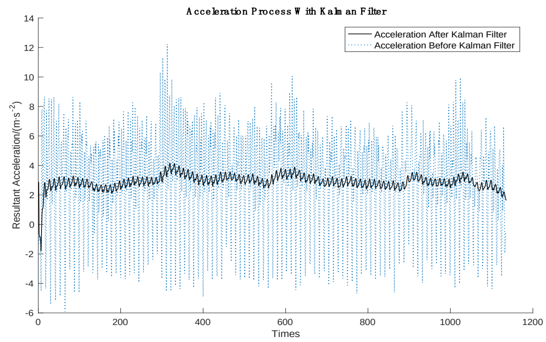


(b)Running in hand 200 steps original data

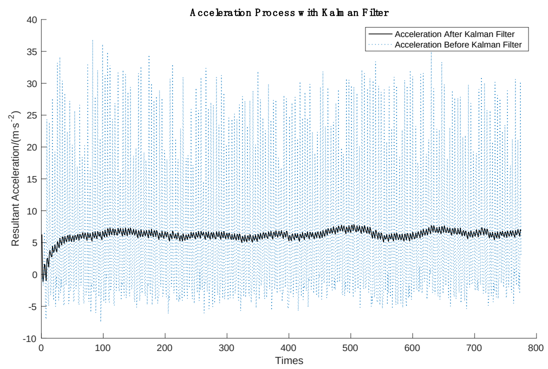


(c)Walking in pocket 200 steps original data

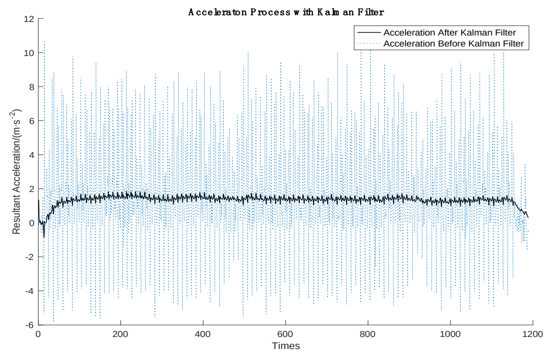
Fig. 6. Three-Axis original acceleration at 3 smartphone states: walking in hand, running in hand and walking in pocket.



(a)Walking in hand 200 steps with KF processed data



(b)Running in hand 200 steps with KF processed data



(c)Walking in pocket 200 steps in pocket with KF processed data

Fig. 7. Acceleration process with Kalman filter at 3 smartphone states: walking in hand, running in hand and walking in pocket.

3.2 App development

We collected the accelerometer data of the volunteer walking through the smartphone MATLAB APP, and verified the algorithm based on the PC MATLAB.

Table 1 *Kalman filter parameters*

Process noise Q	*Observed noise variance R*	*Error variance initial value P_0*
0.000001	*0.0005*	*1*

The simulation results of the three different data are shown in Table 2. The Kalman filter parameter settings are shown in table 1. The Initial state x_0 choose mean value of the all states

***Table 2** The step counting results at three states*

State	*Walk in Hand*	*Run in Hand*	*Walk in Pocket*
Before KF	*181*	*167*	*221*
After KF	*191*	*178*	*249*

3.3 Experimental results

Figure 5 shows the real-time performance based on the peak-of-valley detection algorithm. Because the built-in accelerometer data of the smartphone is easy to obtain, the algorithm has high application value.

Table 2 shows that the Kalman filter-based peak-to-valley detection algorithm shows better performance in all three cases. By comparing the Kalman filter and the Kalman filter acceleration data, the Kalman filter significantly eliminates the false peaks and false valleys caused by the low accuracy of the smart phone sensor. At the same time, the improved algorithm overcomes the errors caused by the random placement of smartphones and different moving rate. It eliminates the number of invalid steps and improve the accuracy to a certain extent. Furthermore, it expands application value in real life.

3.4 Result analysis

The smartphone app offers a number of convenient features for users and makes people's lives extremely convenient. Using the two sensor data of accelerometer and gyroscope in the smart phone, the gait feature can be extracted by time-frequency domain analysis to obtain higher accuracy, but at the same time increase the calculation amount and increase the power consumption [14]. The algorithm based on peak wave trough detection is more easily to implement because of its small amount of calculation, so it has better real-time performance. For this reason, we designed an Android system smartphone APP [15-17]. After the volunteers walking 200 steps in three states, its accuracy reaches 0.94 at least in Table3, and the number of steps can be updated in real time. We only designed a simple interface APP in Android mobile phone to validate the algorithm, as shown in Figure 8. There are two buttons to start counting and resetting steps.

***Table 3** APP results*

State	***Real steps***	***Measuring steps***	***Accuracy***
Walk in hand	200	189	0.94
Run in hand	200	194	0.97
Walk in pocket	200	190	0.95

Fig. 8. The walking in hand 200 steps experimental result based on Android smartphone app, so the experimental accuracy is 94.5%.

4. Summary

This paper proposes an improved algorithm based on Kalman filter for peak-to-valley detection and designed the Android smartphone APP to verify the real-time performance based on the peak wave valley detection algorithm. The preliminary experimental results show that Kalman filter has certain advantages in processing noise data. The acceleration data after Kalman filtering is smoother, which is beneficial to the implementation of the later step counting algorithm. Finally, we collected the real smartphone built-in accelerometer data and verified the superior performance of the improved algorithm in three cases based on the PC MATLAB platform. The results show that the improved algorithm has a higher score when dealing with real life scenes and the step accuracy can basically meet the actual needs of users.

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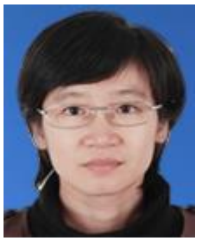

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