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Research article

Running gait pattern recognition based on cross-correlation analysis of single acceleration sensor

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Abstract: As people pay more attention to physical fitness and health keeping, running becomes the first choice for daily sport. However, due to the lack of scientific management and guidance, unreasonable running sometimes has a negative impact on health. The foot strike pattern has a great impact on the knee joint of the runner during running. Therefore, it is important for runners to monitor and record their running gait, so as to customize more appropriate training programs. Through cross-correlation analysis on two axial signals of the acceleration sensor, two common running landing gait patterns, the forefoot strike pattern and the rearfoot strike pattern, can be identified and distinguished. Based on the theoretical analysis, two running gait pattern recognition experiments were designed and conducted. Experiment results reveal that the method proposed can effectively characterize the two running gait patterns and shows a good universality and generalization ability among different subjects.

Keywords: gait analysis; foot strike; wearable device; acceleration sensor; cross-correlation analysis

1. Introduction

According to the World Health Organization (WHO), more than one-fifth of adults are affected by obesity by 2025. Obesity and overweight are the main factors that induce chronic diseases such as diabetes and cardiovascular disease [1]. Scientific and regular physical activity helps to control weight and can effectively prevent various chronic diseases [2]. Since it is a device less, easy to get started, and relatively low cost, running is a popular and simple way to reduce the risk of illness and keep healthy. Related literature has proven that weekly moderate running can significantly lower the risk of coronary, heart disease and diabetes, and has a certain effect on enhancing cardiopulmonary function and relieving psychological stress [3]. In recent years, the people around the world participating in running has been increasing. In 2017, nearly 5 million people participated in marathon events in China, which was 78% more than last year [4].

However, due to the lack of scientific guidance and management, people often neglect the negative effects of running, which directly leads to the incidence of sports injuries as high as 26.0 to 94.2% [5]. At the same time, running is also the main exercise program that induces damage to skeletal muscles such as the tibial muscular and gastrocnemius. During the running process, the human body is subjected to repeated shocks, and the incidence of knee injury caused by the faster pace and excessive running is as high as 7.2 to 50% [6].

Different forms of gait patterns characterize the habitual behavior of individuals in running movements. Gait analysis (GA) as a common method of human gait inspection, can be measured by sophisticated instruments, providing a series of parameters and graphs of kinematics and dynamics, to quantitatively describe and evaluate human gait characteristics [7]. In addition to the field of biological feature extraction and identification, more applications about gait analysis are concentrated in medical diagnosis and kinematics and other professional fields. At present, the main approach to capture human gait data is using high-speed cameras or 3D motion capture techniques in an experimental environment [8]. However, professional gait analysis requires specialized labs, expensive equipment, trained personnel to collect and analyze data during time-consuming processes, which made the traditional gait analysis system is greatly limited for clinical popularization [9]. On the other hand, portable, low-cost wearable devices are becoming increasingly integrated into people's daily lives [10,11]. The wearable gait analysis system is to wear different types of sensors in different parts of the body to record the movement data, through the wired or wireless way to transmit the data, and through algorithms to obtain the gait pattern and status [12,13]. Commonly used sensor types include accelerometers, gyroscopes, magneto-resistive sensors, and force-sensitive sensors. The measurement data and characteristics of each sensor are different. A single type or a combination of multiple types of sensors can achieve different analysis purposes. Obviously, due to the low interference of the wearable measurement unit for the daily activities and outdoor facilitates, it is possible to objectively record gait characteristics in daily life and achieve long-term monitoring to obtain more scientific and comprehensive information [12].

According to the different landing position of the foot, the gait of the human body during running can be regularly divided into two typical gait patterns: the forefoot strike (FS) pattern and the rearfoot strike (RS) pattern [14]. However, no matter which foot strike pattern is adopted, the process of the foot contact on the ground in the stance phase can be subdivided into four successive states shown in Figure 1.

In kinematics, there are differences between the two foot strike patterns, and so are the stress and damage for the joint [15]. The ground reaction force (GRF) on the foot would be transmitted to the bone tissue of the whole body once contacting the ground. Especially for the RS pattern, the heel is repeatedly subjected to GRF to generate larger knee joint torque, which might induce plantar fasciitis, stress fracture of lower limb and knee joint injury [16]. The FS pattern might produce larger ankle joint torque, which may cause foot diseases such as tendinopathy and metatarsal fractures [17].

A clear understanding of the foot strike pattern will encourage people to choose suitable sports equipment and make reasonable fitness plans [18]. The research on human gait pattern recognition has received attention in the fields of business and academics. For instance, NIKE, Inc introduced Nike+, which placed sensors on the shoe plantar to record distance, steps, and calories consumed [19]. In order to explore the differential characteristics between the FS pattern and the RS pattern, Allison et al. conducted an in-depth analysis of the impact on the sole of the foot [20]. Daoud et al. estimated the gait by using high-speed cameras to capture the moment of foot landing and calculate the angle of the foot with the ground [21]. Besides the vision-based, Aminian et al. successfully classified the surface inclination and velocity of human walking using acceleration sensors [22]. Giandolini et al. placed accelerometers on the heel and body of the sneaker respectively and calculated the time between the peaks of the two accelerometer signals by the cross-correlation operation to determine the specific gait pattern [23]. Ma discussed the biomechanical characteristics of different landing modes through an 8-lens infrared high-speed motion capture system and a 3-dimensional force measurement platform [24]. Since most runners' landing gait is mainly rear foot landing or forefoot landing, accurate recognition of these two typical landing gait patterns through a portable device and algorithm has great scientific significance and commercial value. While the existing gait analysis needs professional experimental equipment, the specific location, and high costs. To address that, a simple and feasible foot strike pattern classification method is urgent to promote even for each amateur runner.

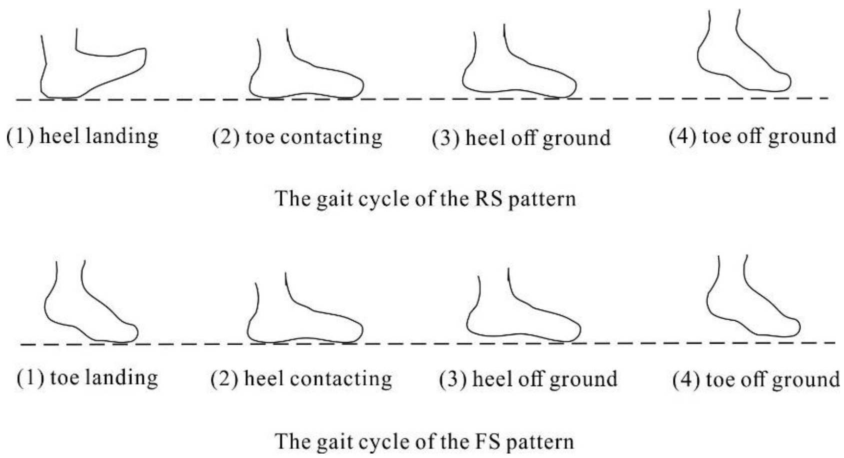


Figure 1. The four foot-states of two gait pattern within a complete gait cycle.

In this paper, aiming at these two gait landing patterns (the FS and the RS), a novel method based on cross-correlation function is applied to realize the recognition of the gait patterns. The gait parameters are collected in real time by a three-axis acceleration sensor built into the sole. Note that no matter which kind of landing pattern is adopted, there are obvious acceleration changes in the forward direction and vertical direction when the foot contacting the ground. Based on that, this paper calculates and analyzes the cross-correlation coefficient of acceleration in these two directions, and proposes a free from location restrictions and low computation algorithm to identify the two gait patterns of the forefoot strike and the rearfoot strike.

2. Materials and methods

Human gait is a series of extremely complex and coordinated movements. The feet contact and leave the ground repeatedly, which can actually be regarded as a kind of approximate periodic motion. In general, a complete gait cycle can be divided into two phases: Stance phase and swing stance, which includes the entire process starting from the foot on one side contacting ground until the forefoot leaving the ground to the foot on the same side landing again. Previous studies have revealed that different runners are affected by different ground reaction forces using different landing techniques according to measuring the ground reaction force with a force platform flushing with the runway surface. There are many factors that affect the impact force on the ground during running, such as the position and speed of the foot at the time of contacting the ground, the effective body mass, the material properties of soft tissue, and shoes that play a cushioning role, etc. Taking the FS pattern as an instance, the forefoot lands first and then the heel touches the ground immediately. After the heel is off the ground, the force exerted by the ground to the foot shifts from the previous gradual increase to the downward trend. And then until the forefoot leaves the ground, the force on the ground disappears. Distinguishing from the FS pattern, the RS pattern will generate an impact peak force within the first 10% of the supporting period at the moment of heel landing [25,26]. Based on Newton's second law, these two gait patterns of running have different characteristic trends in acceleration as well [27].

Based on the ability to represent the FS pattern and the RS pattern with different acceleration variation characteristics, the acceleration sensor is used to acquire the foot acceleration signals in real time. As shown in Figure 2, the toe direction is defined as the *X*-axis direction and the vertical plantar direction is the *Z*-axis direction. For these two different gait landing patterns, Figure 2 shows a diagram of acceleration on the *X*-axis and the *Z*-axis overtime for the period of three complete gait cycles as well.

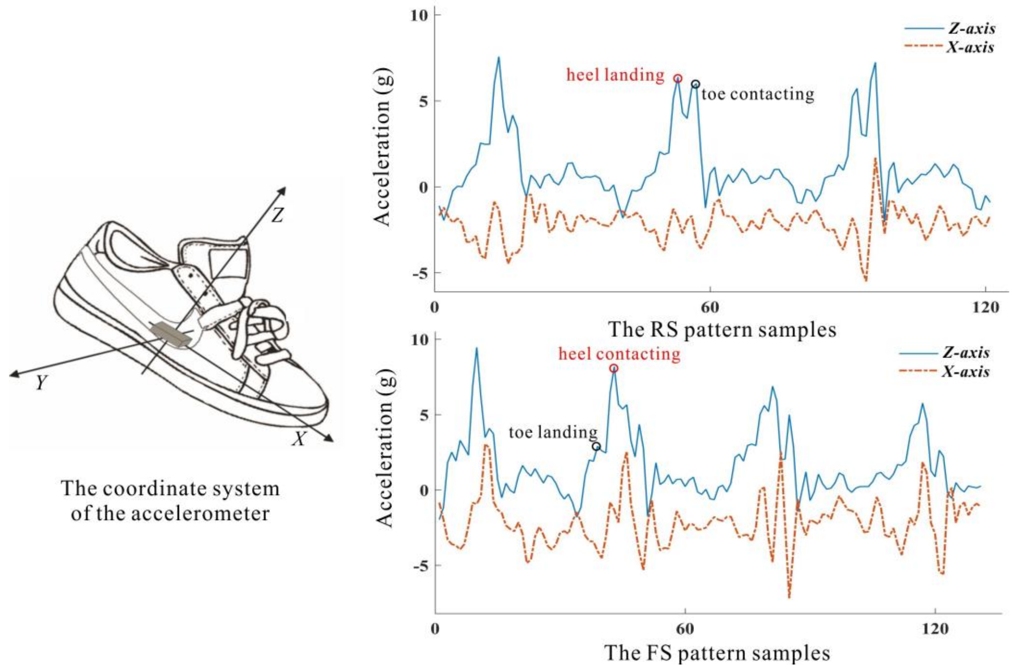


Figure 2. The coordinate system and the acceleration curve graph of the *X*-axis and *Z*-axis going with the time between the FS and RS patterns (potential toe landing point and heel contacting point are marked).

Figure 2. has sketched the relationships of the acceleration in both directions of different foot strike patterns, and the main states in the stance phase have been marked according to the corresponding time. It is clear that the acceleration of each axis generates an obvious peak during the stance phase. Therefore, there is a certain correlation between the two axes of signals. Especially when the RS pattern is adopted, the acceleration signals of the *X*-axis and the *Z*-axis have an obvious negative correlation. The other is that some differences in the timing of the appearance of the acceleration component peaks in the two directions are taken into consideration. Because the FS pattern can form a cushion for the foot when the toe hits the ground, the acceleration component in the *Z*-axis direction will have a small amplitude oscillation before the maximum value appears. Compared

with the RS pattern, the FS pattern may have a relatively large time delay in the presence of peaks in both directions of foot acceleration.

To sum up, the FS pattern and the RS pattern can be characterized by the changing tendency of the acceleration reflected by the foot. The acceleration of the foot in different foot strike patterns is measured by means of a triaxial accelerometer, which contains characteristic information of different foot strike patterns. Based on this, it is effective to use the acquired acceleration signal sequence to realize the pattern recognition. In this paper, the cross-correlation operation of acceleration components in different axial directions is proposed to distinguish the FS pattern and the RS pattern.

2.1. Cross-correlation

The cross-correlation function is a concept in the signal analysis that estimates the degree of correlation between two temporal series, that is, the degree of correlation between two temporal random signals at any two different times in signal processing [28]. Assuming that the two time-domain signal sequences with the same length $\boldsymbol{N}$ are $\boldsymbol{X_{(n)}}$ and $\boldsymbol{Y_{(n)}}$ respectively, the discrete cross-correlation function $\boldsymbol{R(n)}$ with the displacement $\boldsymbol{m}$ is defined as:

$$R_{(x,y)} = X_{(n)} * Y_{(n)} = \sum_{-\infty}^{\infty} \bar{X}_{(\mathrm{m})} Y_{(n+m)}, \tag{1}$$

Where $\boldsymbol{\bar{X}_{(m)}}$ denotes the complex conjugate of $\boldsymbol{X_{(m)}}$. $\boldsymbol{R_{(n)}}$ gives the measure of similarity of the two signals when the lag is $\boldsymbol{n}$.

The cross-correlation of two discrete temporal sequences consists of a series of correlation coefficients corresponding to the displacement $\boldsymbol{m}$. The cross-correlation coefficient is a standard measure to estimate the similarity between the input signals, ranging from 0 to 1. Similarly, a normalized cross-correlation coefficient $\boldsymbol{\rho_{XY}}$ with delay $\boldsymbol{m}$ is described as follows:

$$\rho_{XY}(\mathrm{m}) = \frac{\sum_{n=0}^{N-1}[(X_{(n)} - \bar{X}) \times (Y_{(n-m)} - \bar{Y})]}{\sqrt{\sum_{n=0}^{N-1}(X_{(n)} - \bar{X})^2} \times \sqrt{\sum_{n=0}^{N-1}(Y_{(n)} - \bar{Y})^2}}, \tag{2}$$

As for the cross-correlation sequence, the two temporal signals are best aligned where the $\boldsymbol{\rho_{XY(\mathrm{lag}=\mathrm{m}')}}$ obtains the maximum (or minimum if negatively correlated).

That is to say, the correlation sequence is not completely symmetrical and the position of the sequence peak may occur an offset from the lag location to the central axis of the cross-correlation sequence when two different signals are processed by the cross-correlation function. This offset indicates that the correlation degree of the two columns of signals reaches the maximum when such a phase is changed.

Figure 3 shows a workflow for the analysis and solution of the entire cross-correlation of two sinusoidal signals. The red dot represents the cross-correlation coefficient maximum value with a certain lag. Considering that the influence of lateral acceleration (*Y*-axis direction in Figure 2) can be ignored in any foot strike patterns, this paper proposes to operate the cross-correlation function between the two columns of foot acceleration signals, i.e. the forward direction and the vertical direction collected by a 3-axis accelerometer.

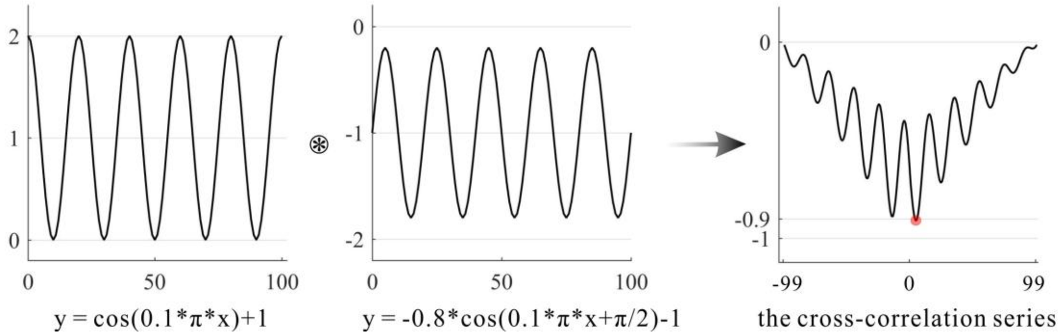


Figure 3. The workflow of the cross-correlation operation.

2.2. Participants

In this study, seven participants were recruited with the convenient sampling method to collect their running gait data. All the participants were in a healthy physical condition without obvious anatomical asymmetry of the lower extremities and used to running at least two hours a week for the last three months. Four participants were asked to run with the FS pattern and the other three were in RS pattern. The basic physical information of these seven subjects was collected and showed in Table 1. Note that the average age was 23.4 and the overall BMI was 20.9 kg/m^2. Meanwhile, inform participants of the experimental procedure and ensure that they were in a resting state before the start of the experiment.

Table 1. The basic physical statistics of the experimental participants.

ID	Gender (M/F)	Age (year)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Required Pattern
1	M	22	170	62	21.5	RS
2	M	26	172	66	22.3	FS
3	F	21	165	48	17.6	RS
4	M	25	174	70	23.1	FS
5	F	23	163	51	19.7	FS
6	F	27	173	60	20.0	FS
7	M	20	174	67	22.1	RS
Mean	--	23.4	170.1	60.6	20.9	--
STD	--	2.64	4.45	8.28	1.90	--

2.3. Data acquisition unit

Considering that the foot strike pattern is to be recognized without affecting daily life, the built-in sensor should be designed lighter, smaller, easier to use and not to change the position placed due to the vibration. On the other hand, the wireless transmission of signals and the lower power consumption are taken into consideration as well. This paper selects LSD4BT designed by the Lierda Co. as the data acquisition unit, which embeds a 3-axis accelerometer. This small module is powered by a button cell and supports Bluetooth 4.0 (Bluetooth transmission technology, high speed, and lower power consumption) shown in Figure 4. In view of the frequency of the daily physical activities is within 20 Hz [29]. Based on this, the accelerometer sensor unit is fixedly placed in the center of the foot of the shoe and collects the acceleration data of the foot in the frequency of 50 Hz. The collected data would be transmitted wirelessly through Bluetooth and persisted into the storage.

Figure 4. The wireless data acquisition unit embedded a 3-axis accelerometer and the placement in a sneaker.

2.4. Validation and analysis

Calculating the cross-correlation coefficients to realize the correlation analysis of acceleration sequences in different directions can provide supportable classification features. That is, the gait characteristic information can be reflected in its correlation coefficients among the different foot strike patterns. The cross-correlation of different acceleration component signals with different characteristics in the forward direction and the vertical direction of the triaxial accelerometer in the same time period is captured and processed, finding that the lag of the maximum value of the cross-correlation sequence exists lag that is from the position of the central axis of this sequence. This lag indicates that when two columns of signals differ by such a phase, the correlation between the signals reaches the maximum. Through the comparison of the offsets, it is found that the two foot strike patterns have obvious differences in the value of their offset. Figure 5 gives the detailed steps of the cross-correlation process of acceleration signals. The acceleration signals of the feet of the participants are collected in real time, and the discrete data points are segmented by a sliding window to intercept the data frames containing complete gait information in order to reduce the calculation amount. Concerning the acceleration signal analysis, a Butterworth low pass filter with a cutoff frequency of 50 Hz has been utilized to reduce the resonant frequency of the attachment [23]. Besides, a fixed 4 seconds length (200 sample points) sliding window without overlapping is adapted to capture gait data of multiple periods. After that, the cross-correlation function of the segmented data frame (data of the same length in the X-axis and the Z-axis) will be executed to obtain a correlation sequence with the length of 399.

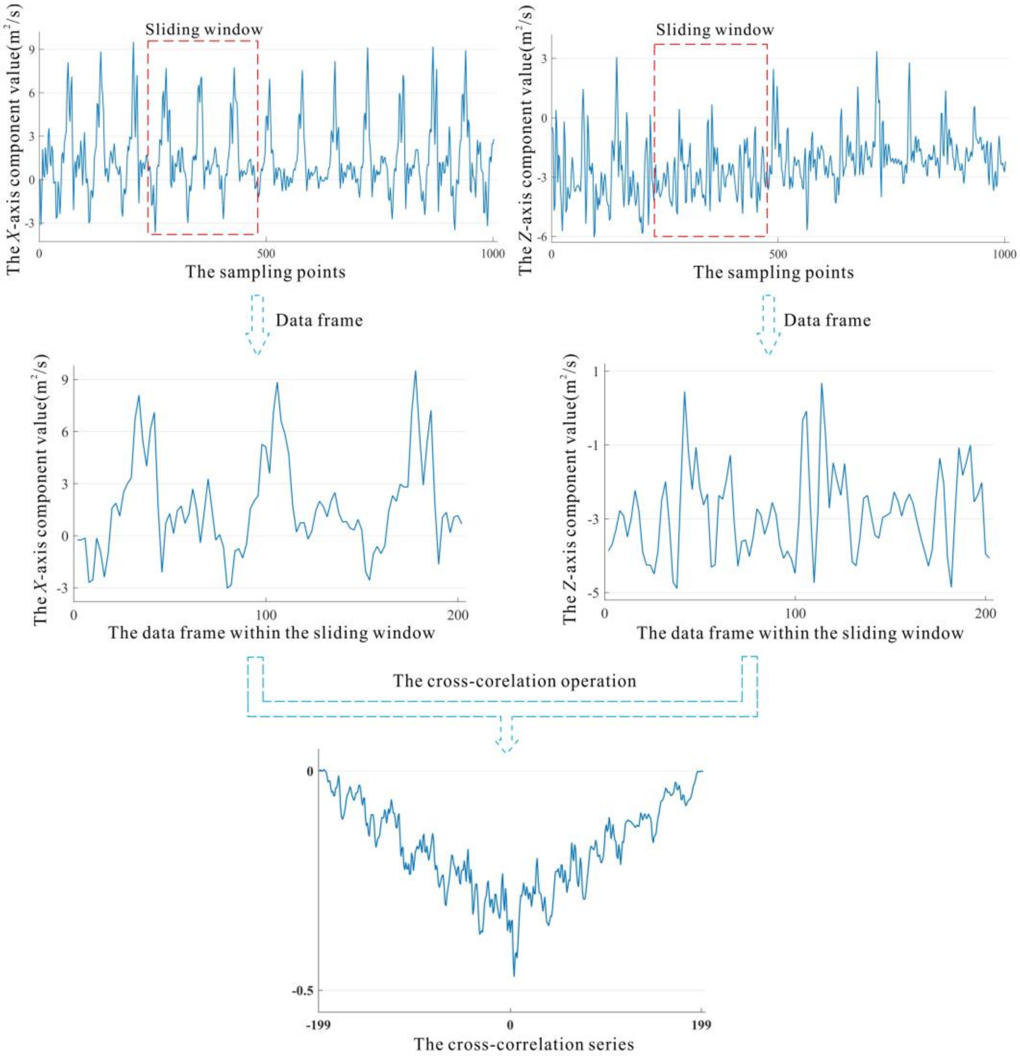


Figure 5. The diagram of the gait data processing through cross-correlation.

The cross-correlation operation is performed on the foot acceleration signals of the FS pattern and the RS pattern respectively. Note that the extreme marked with a red dot in the graph is the feature point of the entire sequence. From the cross-correlation sequence of two foot strike patterns in Figure 6, the extreme value is a negative value, which illustrates that there is a negative correlation between the acceleration in the *X*-axis and *Z*-axis directions of the foot coordinate. To be specific, the acceleration in the one direction tends to decrease when the acceleration in other direction gradually increases.

From the waveform of the cross-correlation coefficient sequence of the two gait patterns, an obvious divergence is mainly reflected in the overall fluctuation of the lag of the feature points, apart from the strength of the vibration amplitude of the entire waveform. It is clear that the offset of the RS pattern is in a smaller range ignoring the direction, while the feature points of the FS pattern fluctuate in a larger range and have a larger fluctuation amplitude. Combined with the acceleration changes of the two gait patterns in Figure 2, the lag degree of feature points of the RS pattern is weaker than that of the FS pattern's when there is a negative correlation between these two signals. Therefore, this paper adopts the cross-correlation coefficient sequence of gaits as the main feature basis to realize the effective recognition of the foot strike pattern.

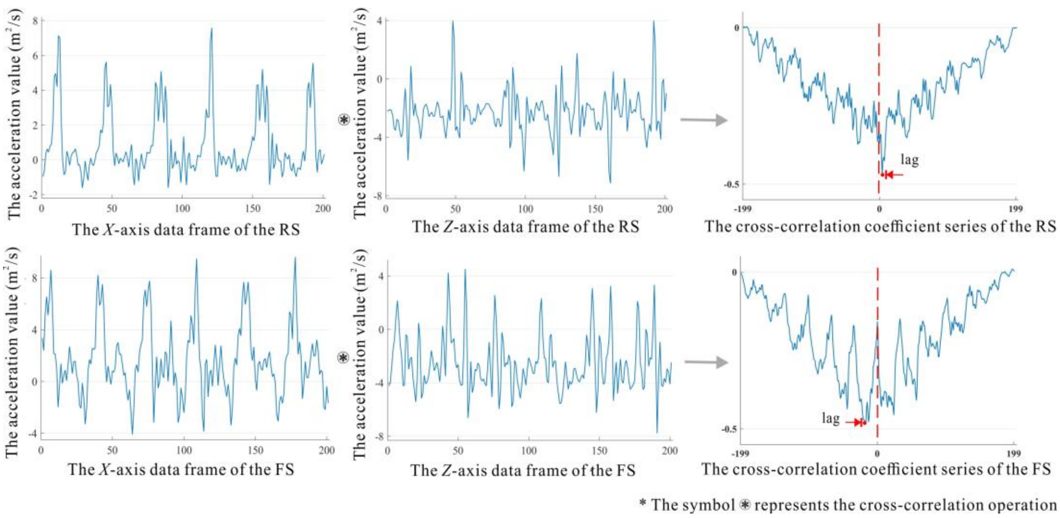


Figure 6. The illustration and comparison of the different offsets between the RS and the FS patterns after the cross-correlation (the sliding window length is 200).

3. Experiments and results

In order to verify the effectiveness of the proposed classification algorithm more comprehensively and reliably, this paper has designed two verification experiments from two different dimensions. The one experiment is conducted to determine all the participants' required foot strike patterns, and the other one focuses on the change process that the same participant performs a random conversion of the foot strike pattern.

All participants were informed that the diet was banned within two hours prior to the start of the experiment. A free-living gait data acquisition experiment was performed about 5 minutes including 3 minutes running state at least. A timer and a speaker were used to ask the participants what kind of gait style they should use and when the gait style should be changed. We would give enough time for the participants to change the gait patterns after the command is given. The participants were required to complete the conversion of the designated foot strike pattern before we started to record the new gait data. The sampling frequency of the accelerometer was set to 50 Hz, and all the information of the extreme feature points of each cross-correlation series would be extracted from the sliding window. These two verification experiments have been described in detail below.

3.1. Experiment Ⅰ

Firstly, this paper has designed a verification experiment for the gait of all participants' preferred. All the participants' foot strike patterns were recognized by calculating the lag feature of the cross-correlation series between the accelerations in the *X*-axis and *Z*-axis directions of the foot. Note that the lag threshold value means the offset distance of the extremum feature point to the central axis of this cross-correlation series. In order to represent the algorithm classification results more specifically and intuitively, the offset threshold of the cross-correlation series feature point has been set to 5.0 to distinguish the two types of foot strike patterns according to the Figure 7.

Table 2 gave the statistical distribution of the degree of deviation of all feature points in the gait experiment, which presented the proportion of points where the feature point offset is greater than the threshold and less than or equal to. It was clearly seen that the data of each participant showed that a certain type of feature points occupied an overwhelming advantage. As for the data from No.2, the FS pattern has been marked, because about 86.67% (the lag threshold is 5.0) of the feature points were higher than the threshold and only 13.33% of the feature points fluctuated within the lag offset threshold through the whole running test stage. Therefore, the required foot strike pattern can be determined by the dominant proportion of the feature points in a certain time period. Similar to the voting method in decision fusion, the pattern of dominant feature points was used as the final classification. Based on that, the feature points larger than the threshold were divided into the FS pattern, and the threshold less than or equal to the threshold was the RS pattern. The experimentally predicted foot strike pattern labels were recorded in Table 2.

Table 2. The distribution of the offset of feature points and the classification pattern.

Participant	Required Pattern	Within *Thr.* (%)	Excess *Thr.* (%)	Predicted Pattern
No.1	RS	***100***	*0*	RS
No.2	FS	*13.33*	***86.67***	FS
No.3	RS	***93.33***	*6.67*	RS
No.4	FS	*9.09*	***90.91***	FS
No.5	FS	*26.67*	***73.33***	FS
No.6	FS	*6.67*	***93.33***	FS
No.7	RS	***100***	*0*	RS

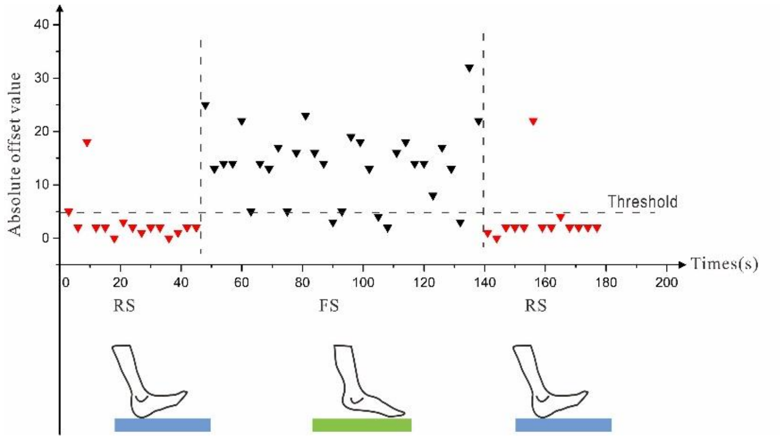
*Within/Excess *Thr*. stands for the offset of the feature point is within/outside the threshold range.

As shown in Table 2, after calculating the offset of the cross-correlation series of all seven participants, the experimental results identified by the algorithm proposed matched correspondingly the real labels. In fact, in order to optimize the classification ability of the algorithm, the selection and determination of the offset threshold can be tuned and more reasonable derivation.

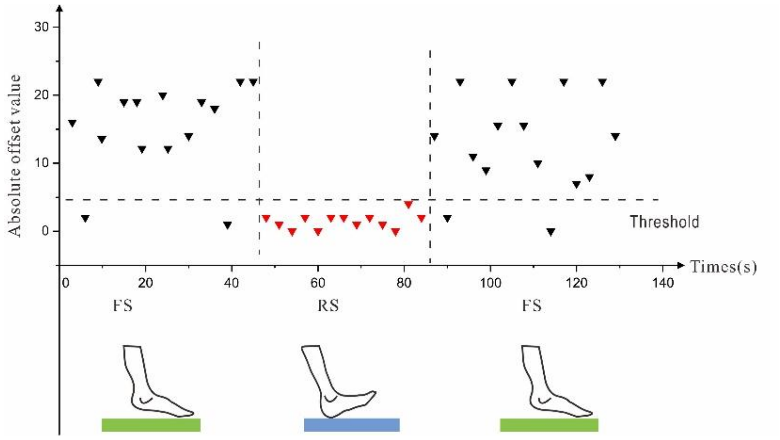
3.2. Experiment Ⅱ

Besides the subject's required foot strike pattern recognition, another experiment has been conducted for the possible foot strike patterns transition of the same subject. In order to ensure the consistency of gait data collection, three subjects who can smoothly switch their foot strike patterns were selected as the test subjects. Allowing adopting one or more certain foot strike pattern arbitrarily for a period of time, three subjects have been chosen to participate in this experiment. And every foot strike state needs maintain at least 1-min running, once the foot strike pattern changes. Note that each participant records the whole foot strike change during the experiment. These three participants perform gait data acquisition experiments for a specified duration in sequence.

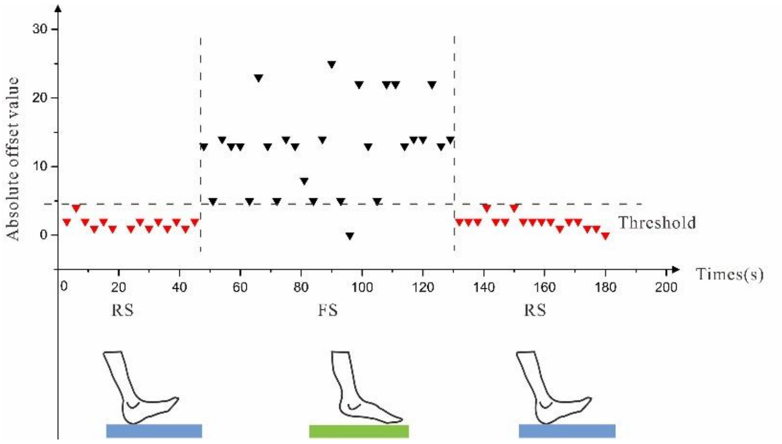
The cross-correlation function has been performed on the three sets of data collected. After operating the cross-correlation sequence, calculate the lag of the maximum feature point of the cross-correlation sequence of each data frame and represent the lag with a dot. Determine the foot



(**a**)



(b)



(**c**)

Figure 7. The distribution of the offset magnitude of the feature points going with time among 3 participants: (a) The distribution of the feature points from sub.1 and the foot strike pattern transformed in RS-FS-RS; (b) The distribution of the feature points from sub.2 and the foot strike pattern transformed in FS-RS-FS; (c) The distribution of the feature points from sub.3 and the foot strike pattern transformed in RS-FS-RS.

strike pattern which the data frame belongs according to the magnitude of the lag. Figure 7 shows the experimental results of three participants. According to the result marked, sub.1 and sub.3 switch from the RS pattern to the FS pattern and finally return to the heels land-contact mode (RS-FS-RS), and sub.2 steps on the forefoot at last after the conversion from the FS pattern to the RS pattern (FS-RS-FS).

Note that the ordinate system indicates the absolute value of the degree of migration, the abscissa stands for the duration of the experiment, and each point represents the deviation of the extreme value feature points of the cross-correlation sequence in each sliding window.

Note that the feature points between the FS pattern and the RS pattern had a distinctly different distribution in the degree of the offset. As shown in Figure 6, the distribution of the absolute values of the feature point offsets among these three participants selected during the experimental period was significantly different, and all the figures reflected two gait changes throughout the process. In Figure 7a,c, the same conversion has been conducted from the heel to the ground mode to the FS pattern and both turned back to the RS pattern. And Figure 7b gave the illustration of an opposite landing order, that is, used the FS pattern for running after converting from the forefoot-contact the ground first to the RS pattern for a while. When the rearfoot was first landing, it could be clearly seen that the offset of the extreme feature points of the cross-correlation series was relatively small. But the offset was obviously fluctuating within a larger range when the FS pattern utilized. An appropriate pre-defined offset threshold, that is, a predetermined offset magnitude, could always be adjusted. Based on that, the specific foot strike pattern can be determined by this offset. When the feature point of a period of time was mainly distributed within the offset threshold, it could be regarded as the RS pattern. While the offset of the feature points distributed beyond the threshold, it could be determined as the FS pattern.

The experimental predictions were consistent with the actual results, which has demonstrated that the lag of the extremum of the correlation coefficient can well represent the characteristics of these two foot strike patterns. The proposed method in this paper discusses the relationship between the cross-correlation and the foot strike patterns and might have a positive effect to differentiate the RS pattern and the FS pattern. Besides, it may allow numerous amateur runners to understand more about running-related injuries and reduce such occurrences.

In summary, the classification algorithm that utilized a 3-axis acceleration sensor located at the sole of the shoe and calculated the cross-correlation series between the acceleration components was proposed to determine the basic foot strike patterns in daily life. And the experiment verification from the different traits of different individuals' foot strike and different gait transitions of the same individual demonstrated that the algorithm was effective and feasible for the pattern recognition during running.

4. Conclusions

In this study, real-time acquisition of human gait data by using low-cost inertial sensors. Compared to the expensive and professional foot strike pattern recognition methods in the laboratory, this paper proposes a novel and lightweight algorithm to identify the FS pattern and the RS pattern basing the cross-correlation. The feasibility of the proposed method was demonstrated by collecting the gait data from different participants and verifying experiments from two dimensions. This work provides a new idea for relevant researchers in the field of gait analysis and makes the foot strike pattern recognition possible outside the laboratory. Believe that athletes and amateur sports enthusiasts will know more about their physical parameters beyond the laboratory restrictions and choose suitable fitness footwear in their daily exercise. Runners will benefit from this gait monitoring system to obtain personalized interaction and effectively avoid some irreversible sports injuries. In addition, the classification algorithm in this paper can finish the operation in the mobile terminal and realize the real-time feedback of the foot strike, which makes the sensor unit as a node integrating the IoT in the vertical market of the smart medical care.

Due to the lack of gait dataset, there is still a shortcoming in this paper. How to achieve input usability and diversification of use, how to achieve more information on the human body need to take into consideration to improve the performance and robustness of the foot strike pattern recognition system. The lag threshold has been given according to the prior knowledge in the experiments, rather than deducing a formal method to obtain a specific value. Future research will strengthen data logging and include a variety of sensors (such as gyroscopes) and more detailed gait patterns like internal and external splayed patterns that cover the areas that have not yet become current research priorities. Provide a more complete real-time monitoring platform for the majority of fitness enthusiasts eventually.

5. Future research

Subsequently, a model will be proposed and set up to recognize the patterns above effectively and automatically. The research of threshold assign will become the author's next concentration. In addition, so as to build the establishment of a health management platform, the classification of toe-in and toe-out will be put into consideration to help users manage themselves more reasonably. In the future, the effects and benefits of the running gait monitoring system for the joint health keeping should be further researched, especially on how to reduce the risk of knee or ankle injuries.

6. Author contributions

All the co-authors have taken responsibility for their own contribution. Lingfei Mo has proposed the whole theory analysis and the experiment design. Lujie Zeng takes charge of data acquisition, algorithm validation (including coding) and paper writing. Mo and Zeng both contribute to the integrity and logic of this work. In addition, grateful thanks are attached to Lierda Technology Co., Ltd. for providing the sensor unit.

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Conflict of interest

No conflicts of interest exist in the submission of this manuscript.

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