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Flexible force sensor for data extraction and dynamic identification of calisthenics' footprint

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Abstract. Gait tactile information includes footprint information and dynamic plantar pressure distribution, which is mainly used in fields such as gait identification, sports science and gait analysis. A flexible force sensor-based method for footprint data extraction and dynamic identification was put forwarded, which was mainly made up of data filtering for plantar pressure, cluster segmentation for single step footprint pressure and dynamic single step footprint identification. Among them, connected domain-based image segmentation method was used to clustering analyze plantar pressure data and single step footprint was identified according to foot anatomy principle. Research results have verified that when walk normally, accuracy rate of data extraction algorithm for single step footprint put forwarded was up to 99 % and recognition rate of dynamic identification method was up to 97 %. Besides, accuracy rate of the algorithm studied for single step footprint extraction of calisthenics was up to 95 %, which was with good robustness.

Key words. Flexible force sensor, calisthenics, footprint data extraction, dynamic identification, cluster analysis.

1. Introduction

With the development of science and technology, method for obtaining plantar pressure information have been developed from footprinting to pressure sensing measurement which used flexible force sensor. Flexible force sensor in large scale can obtain static and dynamic state of plantar pressure, thus no specific steps were needed and walk freely was enough [1]. Plantar pressure data obtained by flexible force sensor was more accurate and practical.

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2. Literature review

Nowadays, flexible force sensor in large scale was used by researchers at home and abroad to obtain static and dynamic plantar pressure data in order to study gait. Flexible force sensor in large scale was used by Yi Xia et al. [2] to study characteristics such as feet Cop track. However, this method was only suitable for identifying footprint of normal walk and not suitable for identifying footprint of dance gait. Pressure measuring insole was used by Christian C. B. Redd et al. [3] to collecting plantar pressure data of feet, with which footprint extraction and dynamic identification was not needed because relevant label has already marked on the hardware of pressure measuring insole. Thus, it processed data rapidly and was free from site limitation.

There were many advantages of collecting plantar pressure data with flexible force sensor in large scale, for example [4] it can collect plantar pressure data of each step of movement and compute time parameter and spatial parameter of gait. Difficulty of this technology was how to process the acquired plantar pressure data. Footprint extraction and dynamic identification of plantar pressure data collected by flexible force sensor in large scale was indispensable. A flexible force sensor-based method for footprint extraction and dynamic identification was put forwarded to tackle above problems, such as limited application fields.

3. Research method

3.1. Platform construction

Platform for obtaining plantar pressure data was designed based on up-to-date data acquisition and control technology. STM 32F single chip was core of hardware acquisition circuit for flexible force sensor, which was mainly responsible for driving linear array canning, controlling sample of analog-digital converter (ADC) and compressing plantar pressure data transmission. Sampling frequency of flexible force sensor was up to 100 Hz. And Ethernet bus mode was adopted to transmit plantar pressure data of lower computer and CMD command of upper computer because a large volume of data was to be transmitted.

Module splicing was adopted to design rectangle platform with length and width measured 8×8 for acquiring plantar pressure data. This rectangle platform was made up of sensor modules of an area of $80\times80\,\mathrm{cm}^2$ on which there were 140×140 pressure sensitive spots in length and width. Every module was an independent sub-system. Data were transmitted through network (Gigabit Switch) to remote PC for processing.

Software for acquiring and analyzing plantar pressure data with flexible force sensor in large scale was designed based on Visual Studio10 development platform. In actual testing, a large volume of data was collected by flexible force sensor. Besides, good real time performance was needed for transmitting, processing and displaying data. Thus, multithread programming was used to program software.

3.2. Method for footprint extraction and dynamic identification

It can resolve (see Fig. 1) plantar pressure data when acquiring it. Mainly, there were 3 steps: filtering plantar pressure data, extracting single step footprint and dynamic identifying single step track. After those steps, plantar pressure data of every step was obtained and parameters such as time, space, movement and dynamics were calculated.

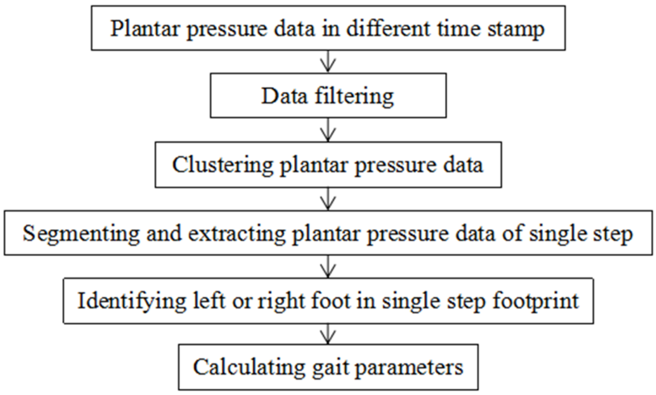

Fig. 1. Resolving steps for plantar pressure data

3.2.1. Filtering plantar pressure data: There was noise jamming during plantar pressure data-acquiring process, which was shown as data noise [5]. Before resolving plantar pressure data, those noises should be filtered out in order to reduce its influence on plantar pressure data. Pressure values on flexible force sensors were classified into 256 grades in order to corresponding it to RGB values. The larger pressure on sensor, the darker color displayed. On the contrary, the smaller pressure on sensor, the lighter color displayed.

Spatial domain filtering, transform domain filtering and morphology noise method were common methods for image denoising. Among them, spatial domain filtering was directly used on original images to tackle gray value of pixel, which included linear filtering, nonlinear filtering, mean filtering, improved mean filtering (MTM), median filtering, and improved median filtering (IMF). Based on MTM algorithm and IMF algorithm, time window [6] conception was introduced to put forward a new filtering algorithm. Principle of the new filtering algorithm was: isolated noise should be deleted using pre-and post-pressure data and IMF filtering algorithm was used to filter the remained plantar pressure data. Flow chart of this algorithm was shown in Fig. 2.

This algorithm was used in filtering experiment for plantar pressure data, and signal noise ratio (SNR) of image [7] was adopted to prove its filtering performance. Thus,

$$\mathrm{SNR} = 10\lg \frac{\sum_t \sum_{\mathrm{row}} \sum_{\mathrm{col}} (\mathrm{Image}_{\mathrm{output}} - \mathrm{Image}_{\mathrm{original}})^2}{\sum_t \sum_{\mathrm{row}} \sum_{\mathrm{col}} (\mathrm{Image}_{\mathrm{addnoise}} - \mathrm{Image}_{\mathrm{original}})^2}\,. \tag{1}$$

In this equation, $\text{Image}_{\text{output}}$ denotes output image after filtering, $\text{Image}_{\text{original}}$ denotes original noise-free image, and $\text{Image}_{\text{addnoise}}$ denotes artificial noise added-image.

Percentage p of impulse noise and Gaussian noise whose standard derivation was σ and mean value was 0 were added to each image. Image SNR was calculated by MTM, IMF and the proposed algorithm and the results are shown in Table 1.

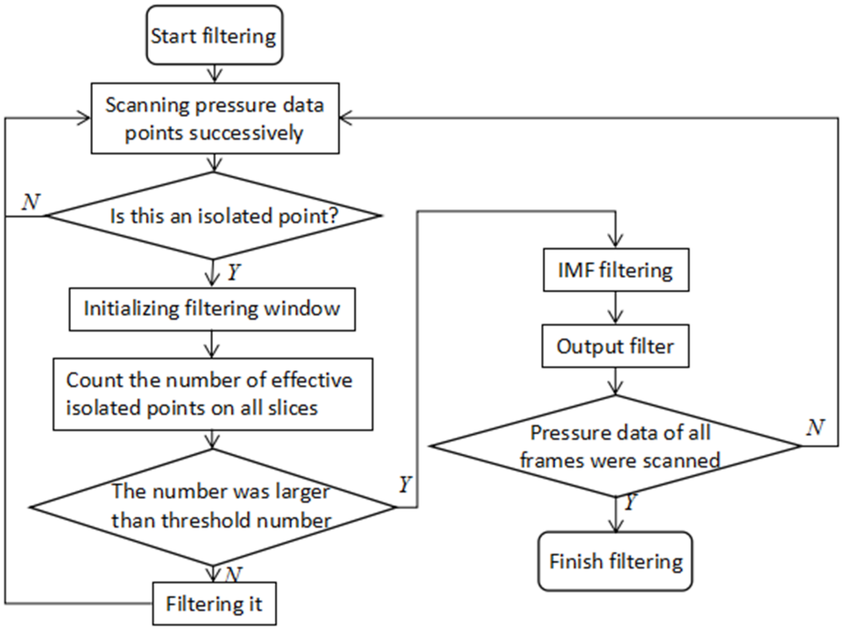

Fig. 2. Flow chart of filtering

Table 1. Denoising effect comparison

Algorithm	MTM	IMF	The algorithm proposed
SNR (dB), $p = 3$, $\sigma = 4$	–8.66	–9.21	–11.82
SNR (dB), $p = 4$, $\sigma = 8$	–9.97	–11.12	–12.51

It can be seen from Table 1 that SNR value of algorithm added with time window was lower than other algorithms, which verified that this algorithm could eliminate noise effectively, save useful data well and avoid useful data be filtered by mistake to some degree.

3.2.2. Data extraction of single step footprint: Plantar pressure data was widely used in fields such as gait analysis and sports science. The key for apply plantar pressure data was extracting gait data accurately. Thus, clustering algorithm was used to extract pressure data of single step footprint. Human normal walk was regular in the aspects of step speed, step length and step width. Plantar pressure data was clustering segmented based on this rule.

Condition 1: In normal walk, step length and step length was changing within a reasonable range;

Condition 2: Feet length and width of normal people was within a reasonable range;

Condition 3: In normal walk, data frame of the same footprint should be within a reasonable range.

Flow chart of segmentation for plantar pressure data is shown as Fig. 3:

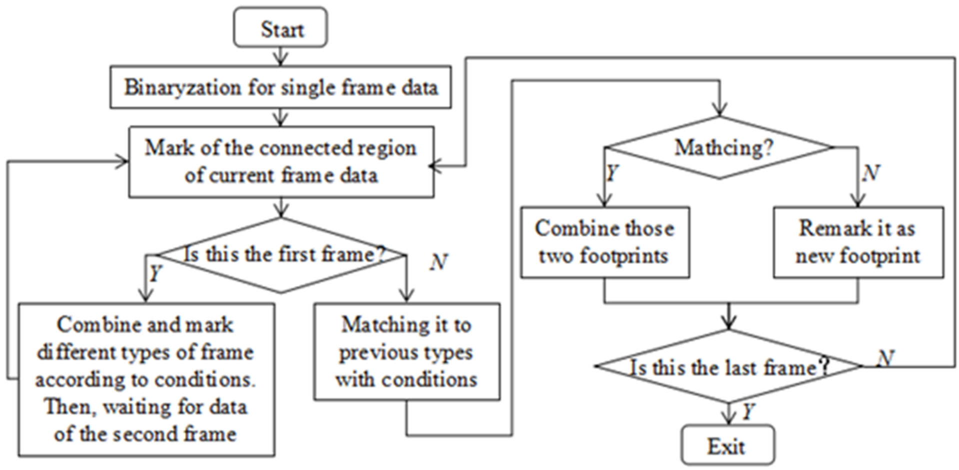

Fig. 3. Flow chart for data clustering

3.2.3. Dynamic identification method for single step footprint: A dynamic footprint identification algorithm based on plantar pressure and footprint outline was put forwarded. The identification steps were shown as follows:

1. Bilinear interpolation algorithm was used to enlarge the original image and median filtering it.
2. Convex hull was used to identify the minimum enclosing rectangle for images in step 1. Included angle of horizontal and vertical direction of footprint was calculated.
3. Image obtained in the step 2 was rotated according to nearest neighbor interpolation, and the long axis was the rotation axis.
4. Morphological processing was applied to the obtained image, which mainly including dilation or erosion action. Then, smoothing filtering was applied.
5. Edge of image obtained in step 4 was extracted with Canny edge detecting algorithm. Convex hull algorithm was reused to calculate the minimum outside envelope rectangle frame.
6. Outside envelope rectangle frame in step 5 was scanned along the direction of long axis. Footprint width in the short-axis and upper and lower boundary points in the vertical direction was recorded. Quartic polynomial data filtering was applied. Besides, regard the upper boundary of the minimum outside envelope as benchmark to record the pixel distance between upper and lower boundary of footprint and the

upper boundary of the minimum outside envelope rectangle frame.

7. In order to highlight crest and trough of fitted curve, range of horizontal axis and vertical axis was compressed to footprint size-long and width.

8. Left or right foot was identified because there were extreme values in footprint width curve and curve of footprint upper and lower points.

Given f_{w}, f_{u} and f_{d} denoting feet width curve, coordinates curve of upper boundary points and coordinates curve of lower boundary points. Local search method was used to solve distribution of extreme value of f_{w}, f_{u} and f_{d}. Given horizontal and vertical coordinates x and y satisfying $y = f(x)$. Steps for searching the extreme points are as follows:

1. $f(x)$ should be calculated from $x = 0$. $f(x + \Delta x)$ should be calculated with step length $\Delta x = 0.02$. Then, curve tendency can be judged.

2. Values of $f(x)$ and $f(x) + \Delta x$ are compared and then $x = x + \Delta x$. If the curve tendency was the same as that of step 1, repeat step 2. If the curve tendency is different from that of step 1, it means there is an extreme point. Record the number of extreme points and their values. Then, $f(x)$ is to express (no accurate value is needed as long as it is near the extreme points) and repeat step 2 until $f(x) = 0$.

3. As for curve f_{w}, the first maximum value f_1 and the second maximum value f_2 should be compared. If $f_1 < f_2$, it means the widest place of footprint is at right. In another word, tiptoe is toward right. If the inequality is opposite, the tiptoe is toward left.

As for curves f_{u} and f_{d}, the number of extreme points should be counted. If the number is 3, it means that there is a great fluctuation in this boundary and it is at the side of medial longitudinal arch. If the number is 1, it is at the side of lateral longitudinal arch. Footprint is identified as long as there is information about the footprint direction and the number of extreme points. The specific computing method is as follows

$$\mathrm{Right} = \begin{cases} f_1 < f_2 \&\& N_{\mathrm{u}} = 3 \&\& N_{\mathrm{d}} = 1, \\ f_1 > f_2 \&\& N_{\mathrm{u}} = 1 \&\& N_{\mathrm{d}} = 3, \end{cases} \tag{2}$$

$$\mathrm{Left} = \begin{cases} f_1 < f_2 \&\& N_{\mathrm{u}} = 1 \&\& N_{\mathrm{d}} = 3 \\ f_1 > f_2 \&\& N_{\mathrm{u}} = 3 \&\& N_{\mathrm{d}} = 1, \end{cases} \tag{3}$$

where N_{u} represents the number of the extreme points on the upper boundary, and N_{d} represents the number of the extreme points of the lower boundary.

4. Experiment and result analysis

4.1. Verification test for extraction accuracy of single step footprint data

Mainly, starting and ending time of single step footprint and coordinates range of single step footprint indicated accuracy single step footprint parameter. Thus, footprint data segmentation experiment for normal walk and calisthenics was designed, and this experiment was divided into normal walk group and calisthenics group.

A line (or list) was randomly chosen on field, on which several rectangle blocks larger than footprint were marked. Besides, distances between rectangle blocks were close to that of step length and step width. The whole test procedure was filmed by vidicon. It was difficult to extract single step footprint data of calisthenics because it was featuring strong rhythm and fast movements. Threshold value for clustering was altered and adjusted correspondingly before extract calisthenics' footprint because there were great different between calisthenics and normal walk. Testing time for calisthenics group was 46 s (a 5 s prelude was included). Testers of normal walk group should step on the rectangle blocks in turn during the test. After acquisition, camera was used to extract, record, and analyze differences between landing time and off-ground time and those filmed by vidicon. In order to further verify the accuracy of the starting and ending time of footprint after partitioning, clustering segmentation algorithm for single step footprint data was used to calculate the starting and ending time of all footprint sequence. The calculated starting and ending times were compared to that of footprint in the video. Then, the frame number of incorrect segmentation was counted and accuracy rate of clustering algorithm was calculated (see Table 2). Footprint segmentation data of normal walk group is shown in Table 3.

Table 2. Footprint segmentation results

Groups	Time	Sampling frame number	Frame number of incorrect segmentation	Accuracy rate
Normal walk group	3 min	18000	96	99.47 %
	5 min	30000	143	99.52 %
Calisthenics group	41 s	4100	162	96.05 %
		4100	168	95.90 %
		4100	170	95.76 %

It is seen from Table 2 that the largest error between footprint range calculated by clustering segmentation for single step footprint data and the pre-planned footprint range was 2 cm, which was within reasonable limits. It also can be seen from Table 2 that in the 3min- and 5min- test for normal walk group, correct system segmentation rate of was up to 99 %. Compared with normal walk group, accuracy rate of footprint data extraction of calisthenics group was relatively lower. Analysis showed that error rate of each step was 1–2 frames because of fast movements of calisthenics. Compared with mean frame number of single step, this error was within the acceptable range because mean frame numbers of each step was 43. It was verified that the put forwarded clustering segmentation algorithm for single step footprint data can identify the starting time, ending time and coordinate range of each step accurately. Plantar dynamics- and connected area-based branching algorithm was suitable for extracting footprint data of normal gait.

Table 3. Footprint segmentation data of normal walk group

Step number	Planned footprint location $(x, y), (x, y)$	Location calculated by system $(x, y), (x, y)$	Starting and ending time of video (ms)	Starting and ending time of system calculation (ms)
1	(10,10),(20,35)	(11,9),(19,36)	1100,2200	1110,2220
2	(45,75),(55,100)	(46,74),(56,99)	2110,2800	2100,2810
3	(15,130),(25,155)	(15,132),(23,157)	2660,3340	2680,3350
4	(45,165),(55,180)	(45,164),(53,188)	3240,3840	3250,3850
5	(15,215),(25,240)	(16,216),(23,243)	3720,4360	3730,4370
6	(40,265),(50,295)	(42,272),(48,298)	4250,4930	4260,4930
7	(15,315),(25,340)	(13,317),(23,343)	4780,5480	4770,5480

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4.2. Verification experiment for dynamic identifying speed of single step footprint

Relevant speed experiments such as fast walk, slow walk, normal walk and walk with variable speed were designed to verify accuracy rate of algorithm for identifying left or right foot. 19 people, walk normally, ranging from 19 to 24 years old were involved in this experiment. All testers were required to walk normally, walk slowly, walk fast and walk in random direction, pose and speed in turn on plantar pressure data acquiring platform. In order to validate the data, this experiment was repeated 4 times. Below it can be found the evaluation criterion.

$$\mathrm{WR}_{(i,j)} = \frac{\mathrm{TR}_{(i,j)}}{\mathrm{FL}_{(i,j)} + \mathrm{TR}_{(i,j)}}\,, \tag{4}$$

$$\mathrm{WL}_{(i,j)} = \frac{\mathrm{TL}_{(i,j)}}{\mathrm{FR}_{(i,j)} + \mathrm{TL}_{(i,j)}}\,, \tag{5}$$

$$\mathrm{W}_{(i,j)} = \frac{\mathrm{TR}_{(i,j)} + \mathrm{TL}_{(i,j)}}{\mathrm{FL}_{(i,j)} + \mathrm{FR}_{(i,j)} + \mathrm{TL}_{(i,j)} + \mathrm{TR}_{(i,j)}}\,. \tag{6}$$

In this equation, $\mathrm{WL}_{(i,j)}$ and $\mathrm{WR}_{(i,j)}$ denote accurate rate of identifying left or right foot when sample i was walking along the jth way. $\mathrm{W}_{(i,j)}$ denotes accurate rate of identifying left or right foot when sample i is walking in the jth way. $\mathrm{TL}_{(i,j)}$ and $\mathrm{TR}_{(i,j)}$ denote correct times of identifying left or right feet, respectively, when sample i is walking along the jth way. Symbols $\mathrm{FL}_{(i,j)}$ and $\mathrm{FR}_{(i,j)}$ denote incorrect times of identifying left or right feet when sample i was walking along the jth way.

As $\mathrm{WL}_j = \frac{1}{N}\sum_1^N AL_{(i,j)}$ and $\mathrm{WR}_j = \frac{1}{N}\sum_1^N WR_{(i,j)}$ are the identification rates for left or right feet when walking along the jth way, $\mathrm{W}_j = \frac{1}{N}\sum_1^N W_{(i,j)}$ denotes mean identification rate of left and right feet when walking along j way. Data acquired when those 19 testers walking according to above process are shown in Table 4.

Table 4. Footprint identification rate

Walking manner	1	2	3	4
AR_j	0.980	0.987	0.975	0.963
AL_j	0.987	0.992	0.975	0.962
A_j	0.983	0.989	0.975	0.963

It can be know from Table 4 that left foot identification rate, right foot identification rate and mean identification rate of left and right foot was relatively high when walking along the first 3 ways. However, when walking along the 4th way, identification rate of left and right foot was relatively lower than that of others walking ways. The reason was that when walking along the 4th way, heel of the testers would sometime off-ground which would influence identification accuracy rate.

Gait characteristic parameters of single step data such as landing time, off-ground time and footprint area were calculated by segmenting, extracting and identifying single step plantar pressure data. Parts of footprint sequence-relevant parameters that calculated with researched method were shown in Table 5.

The study results showed that the researched method featuring high efficiency, high intelligentization and well robustness, identified left and right foot and data fast and accurately.

5. Conclusion

Data about acquiring and applying plantar pressure distribution were analyzed based on flexible force sensor. Besides, plantar pressure data segmentation and dynamic footprint identification method was put forwarded, through which data of left and right feet were accurately segmented and identified and gait analysis and evaluation were more convenient. Further improvement was needed for the researched clustering analysis algorithm and method for identifying left and right feet, such as improved footprint identification rate and clustering conditions.

Table 5. Part of relevant parameters of each step in footprint sequence

Steps	Left/right foot	Landing time (ms)	Off-ground time (ms)	Footprint area (cm^2)	Hang time (s)	average pressure value of single frame (N)
1	Left	770	1650	145	0	604.5
2	Right	1510	2170	150	0	574.8
3	Left	2080	2710	148	0.42	576.1
4	Right	2700	3210	154	0.42	557.9
5	Left	3050	3720	148	0.37	612.1
6	Right	3590	4210	146	0.38	580.2
7	Left	4090	4800	150	0.35	596.2
8	Right	4580	5180	149	0.36	587.0

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