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▶ **To cite this version:**

Ruijun Liu, Zhang Bohua, Yu Zhuo, Han Zhiyuan, Wu Jingbang, et al.. Vibration-based Terrain Classification Recognition Using a Six-axis Accelerometer. Computers and Electrical Engineering, 2021, 96 (part B), 10.1016/j.compeleceng.2021.107556 . hal-04317498

**HAL Id: hal-04317498**
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Submitted on 1 Dec 2023

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# Vibration-based Terrain Classification Recognition Using a Six-axis Accelerometer

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## ABSTRACT

Aging is a key problem in our daily life which demands more technology such as the terrain classification recognition for the detailed path planning. In this article, a six-axis accelerometer was placed on the base of a walking stick to capture walking gait vibration information. The signal features in the collected information were used to reflect the terrain. We used a matching tracking method to decompose the signal data into linear combinations of Gabor atoms and a joint time-frequency analysis method to perform analysis on the topographic features in a three-dimensional space. Three types of terrains were classified from space-time data. Results show that the proposed algorithm could achieve an average accuracy rate of 88.6%, which is 4% higher than conventional methods.

**Keywords:** vibration, terrain classification, Gabor atomic decomposition, time-frequency analysis

## 1. INTRODUCTION

Nowadays, ageing problem has become increasingly serious with the changes in population structure and the significant increase in life expectancy [1]. In particular, elderly people who are ill and have mobility problems should be aware of the detailed terrain of the walking route before going out to avoid high-risk walking movements, such as uphill, bumpy or downhill terrain features. In order to achieve that, the detailed terrain data should be collected and classified beforehand. In this paper, we utilize a high reliable, small sized and facilitate integrated six-axis accelerometer, which is a MEMS-based sensor and can meet characteristics of autonomy and portability. The sensor is tied on a walking stick to collect the terrain data while people walking. After the data is collected, we extract different acceleration parameters to help identify these terrains. In order to collect the gait acceleration signal, we set up a device combining the accelerometer and the storage device, and input the signal into the algorithm model to extract the terrain category step by step, and finally get the experimental results. Specifically, we use Wigner-Ville Joint Time Frequency Analysis (JTFA) to study triaxial accelerometer signals (the time-domain and frequency-domain extended signals are often used to analyze nonstationary time series [12]), and to extract the distribution of JTFA features by principal component analysis (PCA) which is used to train and classify the effects of different terrains on gait behavior. Through the proposed method, the recognition accuracy and robustness of the algorithm can be improved.

## 2. RELATED WORK

At present, the methods of detection of terrain analysis can be mainly divided into two types. The first type of method uses human gait information or terrain distribution image obtained by video frames. In [1]-[5], different types of topographic relief features or motion track information features were extracted from surveillance video. These functions were used for terrain detection and analysis. The method of detecting terrain based on video frames has some difficult problems to overcome, such as the limitation of the number of cameras, installation positions, and camera capture views, which greatly limit the practical application of such method. The second type of method uses movement data collected and analyzed by wearable devices and related detection devices. [6]-[13] utilized explore gravity acceleration sensors or gyroscopes for terrain detection. [6] used iPhone-based accelerometer and gyroscope to analyze gait characteristics of different terrains. In [7], the subjects' gait data was acquired by a Wall-mounted motion recognition system, and machine learning algorithms were used to identify the gait to derive terrain features. Tong et al. [8] proposed a method based on Hidden Markov Model (HMM), which used a six-axis acceleration of the human body to detect terrain. David et al [9] introduced the design and implementation of hardware and software for a low-cost wearable system to monitor and retrieve information of human activity. In [10], the authors used inertial sensors (3D accelerometer and gyroscope) carried by a trunk and thigh wearable system. The system operated on a generated countermeasure network (BAN), which makes the users more comfortable for long-term wear. Birdal [11] reported that a key factor to analyze gait video is the combination of acceleration information in different dimensions. According to that, we can extract health features from 3d gait data to identify different human gait patterns. Some of the above methods require people with limited mobility to carry extra sensors to record their walking which increases their difficulty in walking. In addition, the related works in [14]-[17] involve Artificial Intelligence (AI), which are of great significance.

The study of gait analysis in this paper mainly focuses on the recognition of gait in different terrains. The analysis is based on collecting walking data in a way that does not add additional burden for walking prediction. People with limited mobility usually uses walking sticks. Our portable sensors are installed on the walking sticks to record walking data. Next, based on the characteristics of this data, a machine-learning classifier is used to make behavioral predictions.

## 3. ABNORMAL BEHAVIOR CLASSIFICATION METHOD

### 3.1 Data collection

In the proposed algorithm, we connect a six-axis acceleration module to the Arduino UNO which is a microcontroller board, to measure and store the walking movement data (XYZ three-axis acceleration data). The data is recorded during a user's walking, and then transferred to the computer through a data transmission module. Next, a Kalman filter fusion algorithm is used to process acceleration data on the PC side. Finally, the collected data is integrated and classified using the Gabor atomic decomposition algorithm to determine the range of acceleration parameters corresponding to different terrains.

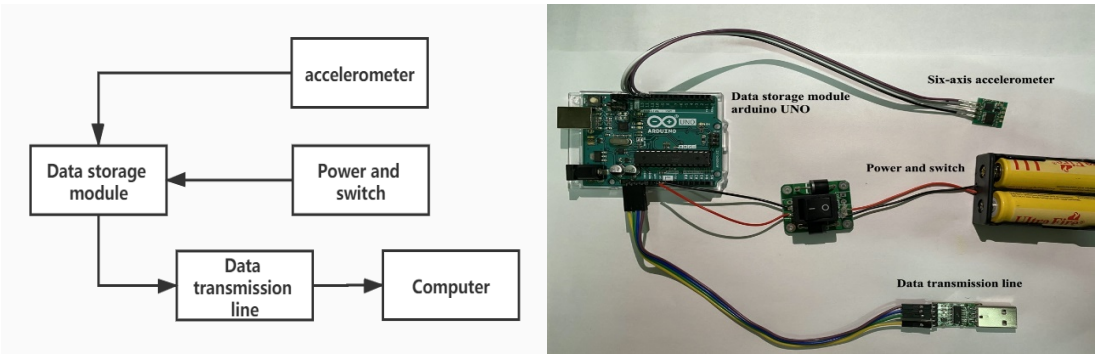



Figure 1. Terrain recognition device based on accelerometer

### 3.2 Data preprocessing

The embedded six-axis accelerometer described in Figure 1 can collect the acceleration data caused by human motion of X, Y and Z axes respectively. For different motor behaviors, such as uphill, downhill, and upright walking, the acceleration data is completely different.

To minimize the error caused by the initial installed position of the accelerometer, the amplitude of the signal vector is defined as formula (1):

$$SVM(t) = \sqrt{X^2(t) + Y^2(t) + Z^2(t)} \tag{1}$$

X(t), Y(t), Z(t) represents the acceleration of the three axes respectively.

Before the SVM feature extraction, the masking threshold constraint Kalman filter is used to enhance the acceleration signal. The sample process of the n-th cleaning acceleration signal s(n) is simulated as follows:

$$s(n) = \sum_{i=1}^{p} a_i s(n-i) + u(n) \tag{2}$$

Here $p$ is the sample number, $a_i$ is the i-th coefficient, $u(n)$ is the residual signal, and s(n) is assumed white noise with variance ${\sigma^2}_u$. As shown in Figure 2, after data preprocessing, the accuracy of the data is effectively enhanced, which is more in line with human gait characteristics. In particular, in the case of low SNR, the readability of the data is better.

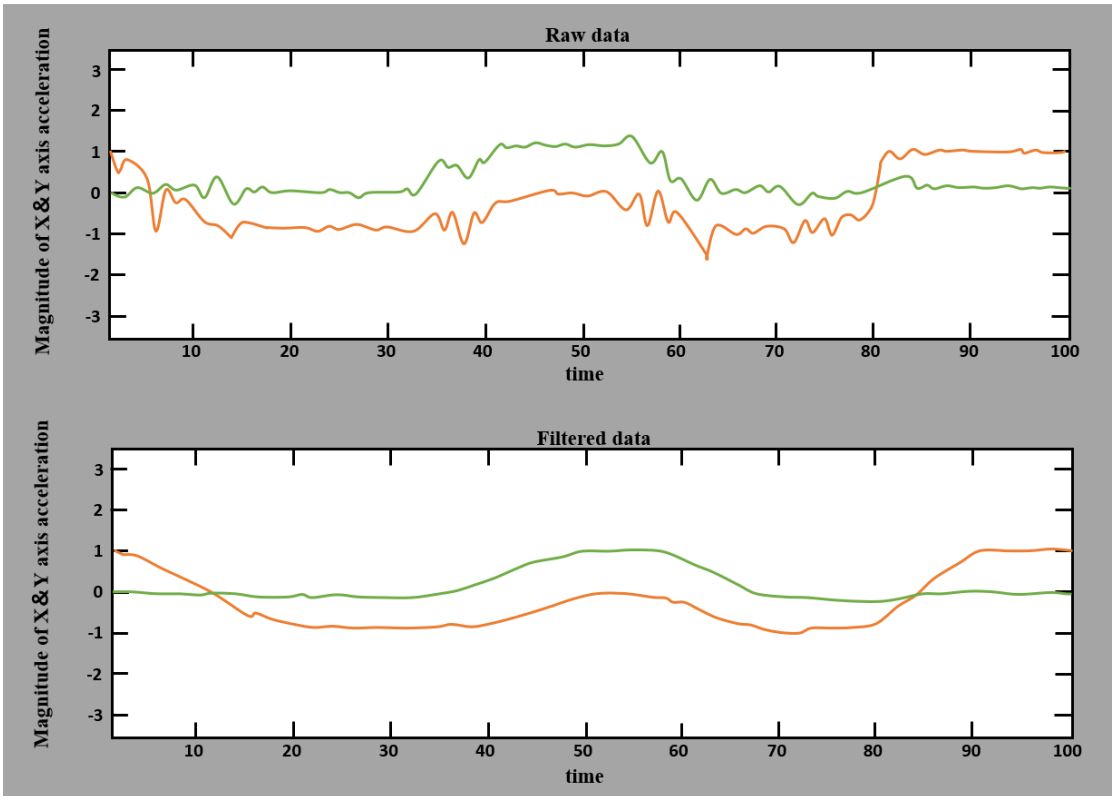



Figure 2. Comparison of acceleration before and after data denoising

### 3.3 Feature Extraction

During the training, it is necessary to collect and understand the vibration signal characteristics of the three types of terrain involved in this paper. Therefore, during the experimentation the user has to walk with the stick at six different speeds on three preset terrains to obtain the vibration information. The walking stick was equipped with a 100 Hz six-axis accelerometer. In order to facilitate the processing of experimental data, the collected data was divided into several segments. We can acquire 6 by 100 vectors per second, and the data was labeled according to the different terrain.

For the sake of data processing, we standardized the data, and normalized the vector in each direction of vibration to a vector with a mean of 0 in 100 dimensions and then took the Fourier transform. Standardization reduces the influence of incorrect data on the final result, which is beneficial to the accuracy of the final result. After the normalization of the data, each indicator is in the same order of magnitude, which makes the evaluation results more comprehensive and improves the accuracy.

Common feature extraction algorithms, such as HOG (Histogram of Gradient) feature extraction algorithm [7] and SIFT (scale-invariant feature transform) local feature detection algorithm [13], have good performance in vibration feature extraction, but under the time efficiency, there is a large space for improvement. In this paper, a Gabor atomic feature extraction algorithm based on MP is introduced. MP is a nonlinear iterative process, and the signal is decomposed into linear sums of known Gabor functions [13]. The decomposition of MP is realized through algorithm iteration. The number of iterations is determined by the residuals of the data. Firstly, the initial function value G selects (D) from the data to have the maximum function value. Next, the difference between the characteristic signal and the input signal is calculated. In a continuous iteration, the value of the Gabor function with the

maximum product of the new given signal is selected. This process is repeated until the signal reaches target accuracy. The above steps can be defined as:

$$\begin{cases} R^0 x = x \\ R^n x = \langle R^n x, g_{\gamma n} \rangle g_{rn} + R^{n+1} x \\ g_{\gamma n} = argmax\, g_{rn \in D} \left| \langle R^n x, g_{\gamma i} \rangle \right| \end{cases} \tag{3}$$

where $x$ is the signal atom. In the n-th alternations of MP, the atomic iteration signal $x$ is expressed as $g_\gamma$, and the difference of n-th is regarded as $R_n$. The number of alternations is $M$. The final $x$ iteration result can be expressed by the following formula:

$$x \approx \sum_{n=0}^{M-1} \langle R^n x, g_{\gamma n} \rangle g_{\gamma n} \tag{4}$$

Gabor function is used to analyze the time and frequency of different acceleration signals:

$$g_{\gamma n} = K(\gamma) e^{-\pi \left( \frac{t-u}{s} \right)} cos(2\pi f(t-u) + \varphi) \tag{5}$$

$\gamma = (u, f, s, \varphi)$ is the time-frequency parameter. There are many factors that can affect it, including displacement, frequency, velocity and amplitude of vibration.

After summation of the WVD (Wigner-Ville Distribution) of the selected Gabor function, the time-frequency distribution of the acceleration signal can be obtained:

$$Ex(t, f) = \sum_{n=0}^{M} \left| \langle R^n x, g_{\gamma n} \rangle \right|^2 W g_{\gamma n}(t, f) \tag{6}$$

Then, the WVD matrix with time-frequency distribution is extracted as the feature by the algorithm in order to realize the recognition and classification of different terrains.

Currently, vibration-based terrain classification methods are only based on vertical (z-axis) detection. The main reason is that the vertical acceleration is most sensitive to the terrain change and the change is the most obvious one. In order to further improve the recognition accuracy, we introduced the measurement of horizontal acceleration, that includes forward and backward (x-axis) direction, and left and right (y-axis) direction. By introducing these two dimensions of data, we can find the best feature recognition results in multi-dimensional data and different terrain.

In this paper, we collected the vibration data during a period of 1.5 minutes under three different terrains. According to the above method, 90 sets of data were collected for each terrain, thus 270 sets of data were collected in total. During the training process, 80% of the data were randomly selected for training, and the rest 20% of the data were used to test the accuracy of classification.

### 3.4 BP Artificial Neural Network Training

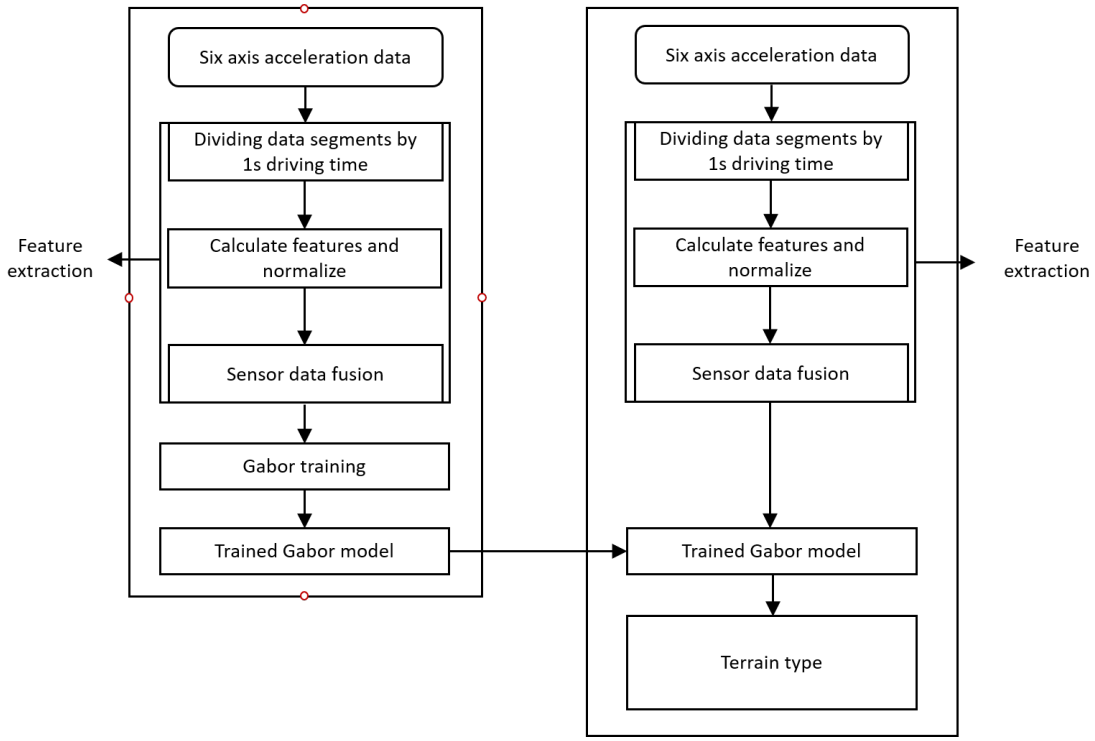



Figure 3. Flow chart of terrain classification algorithm based on vibration

The training process will be divided into two parts shown in Figure 3. In the training process of the model, we firstly preprocessed the collected data for noise reduction, and then used the algorithm mentioned above to obtain the gait features after fusion as input to the BP neural network for learning. It is worth noting that because different walking sticks users may have different walking characteristics, the neural network can be used to effectively learn terrain features without being disturbed by the behavior patterns of different users. Later, in the test part, we used the walking data as the input system to get a three-way classification output as the terrain classification.

In order to classify three kinds of terrain, we also designed a three-layer BP neural network. The input layer is made up of 300 neurons in order to adapt to the corresponding input vector. The hidden layer contains 18 neurons, which corresponds to three different terrains in the experiment, so there are three neurons in the output layer. After the training process, the neural network can carry out actual classification and collect unknown signals based on the experimental platform. The signal contains the 1×300 vector generated by the acceleration signal detected in three directions per second. After normalization and standardization, features were extracted with Gabor and then classified by trained neural network, and finally the evaluation results of terrain types were obtained.

## 4. EXPERIMENTS

### 4.1 Methods

The terrain classification experiment system includes a walking stick, a JY61 serial six-axis accelerometer/gyroscope, an Arduino board, a power supply (6v) and a switch, a USB transmission

device, a 32G storage device, and a laptop computer. As shown in Figure 4, the total weight of walking stick and equipment is 0.76kg. A six-axis accelerometer/gyroscope is installed near the bottom of the walking stick. Acceleration data is automatically collected and stored during the user's walking. After that, the experimental data is read and imported into a computer for further analysis.

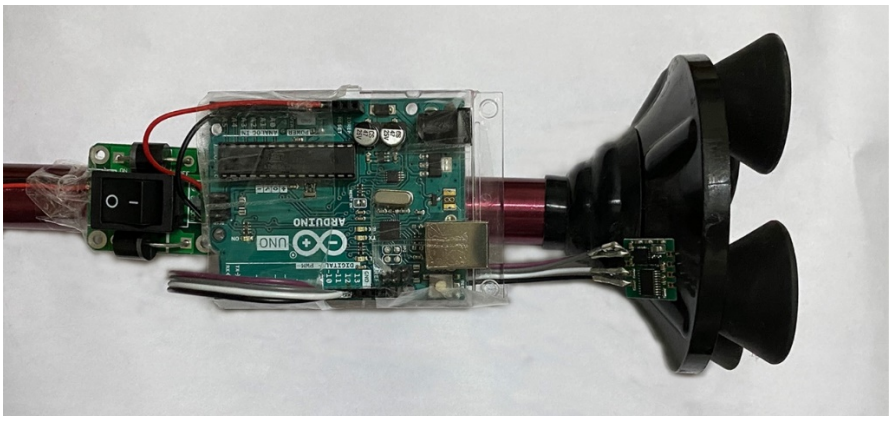



Figure 4. Instrumented walking stick.

The experimental terrain is divided into three types: straight cement pavement, inclined 30° uphill, and inclined 30° downhill. The schematic diagram of the experimental terrains is shown in Figure 5. We counted the walking speed using a speedometer in the experiment. The user was asked to walk back and forth uniformly on the three types of terrain at six speeds respectively, *i.e.*, 0.6m/s, 0.8m/s, 1.0m/s, 1.2m /s, 1.4m/s, and 1.6m/s.




Figure 5. The terrain kinds in experiments

### 4.2 Results

When the walking stick moves on the three types of terrain, different acceleration signals will be generated dues to the different interactions between the walking stick and the ground. As shown in Table 1, we can see that the triaxial accelerometer data differs more on straight road.

The average value of the X-axis acceleration approaches 0, which is relatively gentle. The peak and range display show that the X-axis acceleration has a smaller vibration amplitude. The Y-axis acceleration has a negative mean value, and the highest peak value and range error, which indicate that the acceleration in the Y-axis direction changes greatly even when the road surface is gentle. The average value of the Z-axis acceleration is positive, the peak value and range are small, which indicate that the Z-axis acceleration changes smoothly on a smooth road. In the uphill slope of 30 degrees, the acceleration in the X-axis direction changes significantly, the average value is large and a significant

peak appears and the peak in the Y-axis direction is positive, which indicate that the walking stick swings greatly in the Y-axis direction, and the acceleration in the Z-axis direction is still stable. In a downhill slope of 30 degrees, the average acceleration in the X-axis direction is negative, the peak value is low, and the range is enlarged; the acceleration fluctuation in the Y-axis direction is huge, and it is obviously close to the same direction; the acceleration of the Z-axis acceleration is violent, the range is enlarged and the direction.is consistent. When downhill, it shows that the Z axis acceleration vibration amplitude is large and the direction is the same. It is not difficult to find through the chart. Each type of terrain generates a unique acceleration signal, allowing the computer to identify each type of terrain and then process the data before classifying it with an algorithm.

| **speed 1m/s** | **Straight road** | | | **Slope 30 degrees uphill** | | | **Slope 30 degrees downhill** | | |
|---|---|---|---|---|---|---|---|---|---|
| **Direction of acceleration** | **mean value** | **peak** | **range** | **mean value** | **peak** | **range** | **mean value** | **peak** | **range** |
| **X axes** | 0.07 | 0.63 | 1.26 | 0.37 | 01.23 | 1.46 | -0.12 | 0.78 | 1.67 |
| **Y axes** | -0.12 | -1.12 | 2.21 | -0.26 | -1.13 | 1.32 | -0.56 | -1.33 | 2.62 |
| **Z axes** | 0.11 | 0.8 | 0.96 | 0.07 | 0.35 | 0.67 | -0.23 | -1.15 | 2.13 |

Table 1. Different terrain and corresponding gait data (1m/s)

It can be seen from Figure 6 that the average accuracy rate of classification of a single sensor data is between 50% and 80%. Overall, the average accuracy rate of classification in the z-direction acceleration is slightly higher than that in the x-direction and y-direction. But it is always lower than the average accuracy of the classification of the three sensors. Because the fusion of 3 sensors can make use of the advantages of each sensor thereby improving the average accuracy of classification.

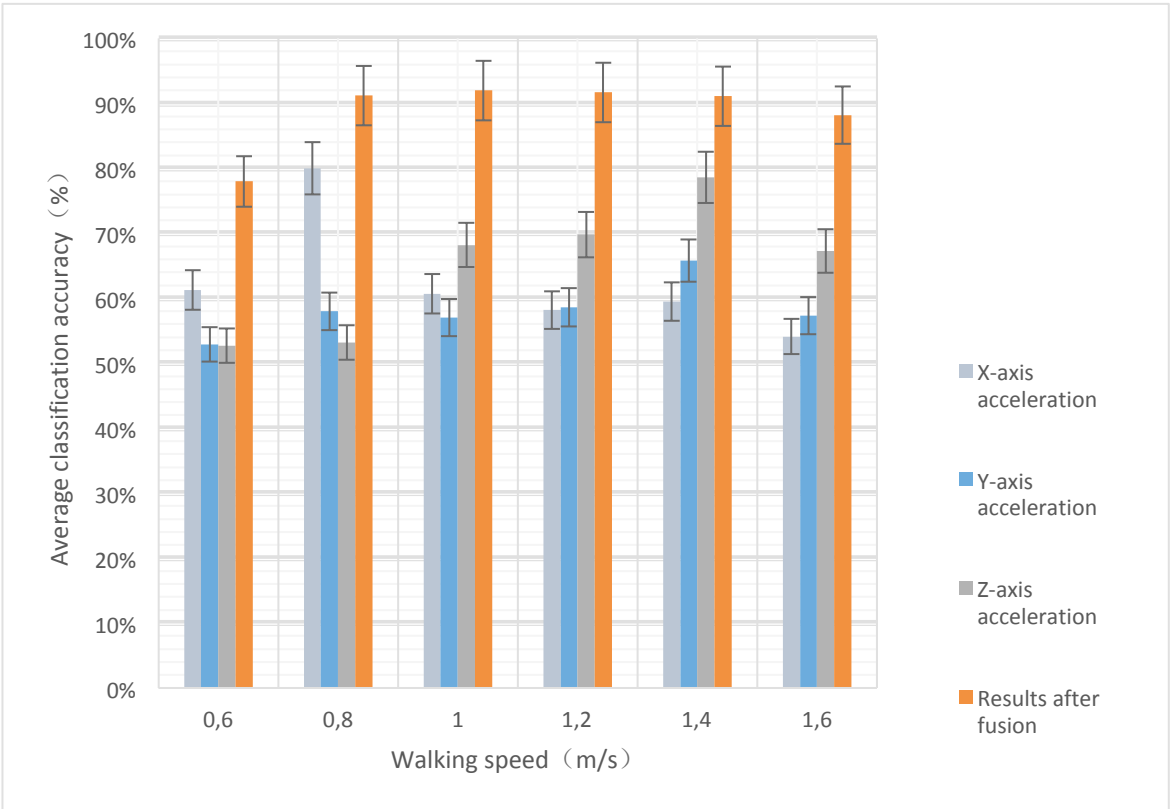


Figure 6. Comparison of classification result from different sensors' data at six walking speeds.

By calculating the average classification accuracy, we compared the algorithm with the SVM algorithm. At medium and high speeds, the accuracy of our algorithm can reach more than 90%, which is higher than the SVM algorithm, as shown in Figure 7. At the same time, it can be seen that at the six speeds, the average accuracy of our algorithm finally reached 88.6%, which is about 4% higher than the traditional SVM algorithm.

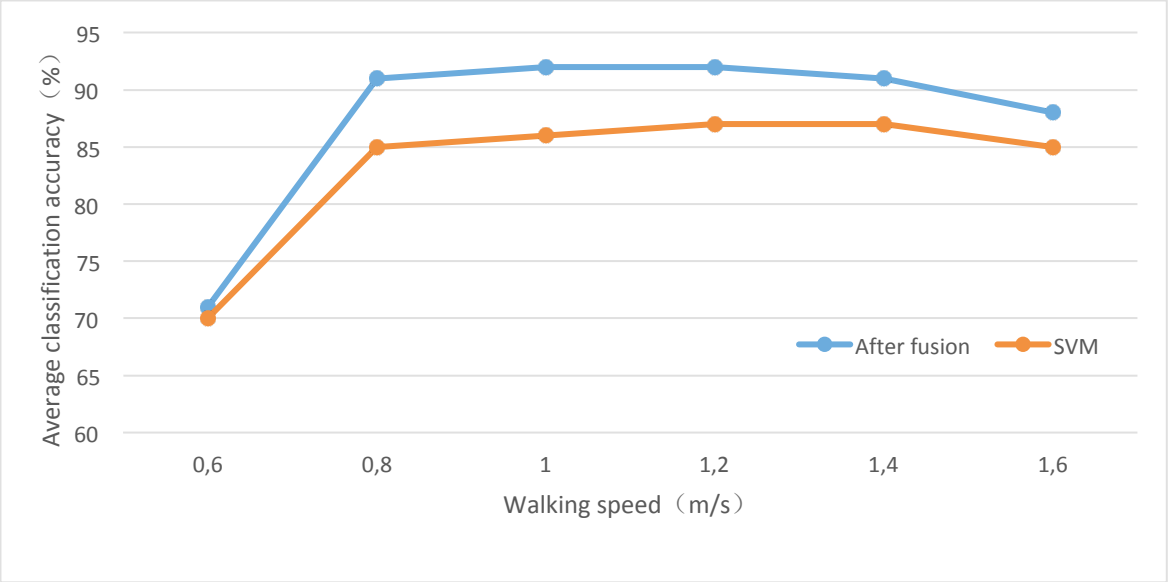



Figure 7. Comparison of classification results.

## 5. CONCLUSION

In this paper, a terrain feature analysis method based on a six-axis acceleration sensor is designed and implemented. The detected acceleration signal is extracted and analyzed with Gabor atomic features, so as to classify different terrain in a three-dimensional space. The average classification accuracy of the experimental platform is 88.6% under six types of speeds. The experimental results prove that the accuracy of classification can be improved by analyzing the data acquired from the accelerometer. In the future work, we will consider more sensors to obtain data, and apply the latest artificial intelligence methods to analyze the experimental results.

## 6. ACKNOWLEDGMENTS

This research was funded by the Beijing Natural Science Foundation grant number (4202016), National Natural Science Foundation of China grant number (62076012, 61972010), Research Foundation for Youth Scholars of Beijing Technology and Business University, PXM2020 014213 000017, QNJJ2020-27.

## REFERENCES

[1] Berns, K. and Mehdi, S. A., "Use of an Autonomous Mobile Robot for Elderly Care", Advanced Technologies for Enhancing Quality of Life, pp. 121-126, 2010.

[2] Saad, A., Zaarour, I., Guerin, F., Bejjani, P., Ayache, M. and Lefebvre, D., "Detection of freezing of gait for Parkinson's disease patients with multi-sensor device and Gaussian neural networks", Int. J. Mach. Learn., vol. 8, no. 3, pp. 941–954, 2017.

[3] Zhang, D. P., Peng, H. L., Yu, H. B. and Lu, Y. F., "Crowd abnormal behavior detection based on machine learning", Information Technology Journal, vol. 12, no. 6, pp. 1199-1205, 2013.

[4] Chen, X., Weng, J., Lu, W. and Xu, J., "Multi-gait recognition based on attribute discovery", IEEE Trans. Pattern Anal. Mach. Intell., vol. 40, no. 7, pp. 1697–1710, 2017.

[5] Chen, X., Yang, T. and Xu, J., "Multi-gait identification based on multilin-ear analysis and multi-target tracking", Multimedia Tools Appl., vol. 75, no.11, pp. 6505–6532, 2016.

[6] Sun, B., Wang, Y. and Jacob B., "Gait Characteristic Analysis and Identification Based on the iPhone's Accelerometer and Gyrometer", Sensors, vol. 14, pp. 17037-17054, 2014.

[7] Nandy, A., Pathak, A. and Chakraborty, P., "A study on gait entropy image analysis for clothing invariant human identification", Multimedia Tools Appl., vol. 76, no. 7, pp. 9133–9167, 2017.

[8] Kozlowski, P. and Walas, K., "Deep neural networks for Terrain recognition task", Proc. Baltic URSI Symp., pp. 283-286, 2018.

[9] Lishani, O., Boubchir, L., Khalifa, E. and Bouridane, A., "Human gait recognition based on Haralick features", Signal Image Video Process., vol. 11, no. 6, pp. 1123–1130, 2017.

[10] Singh, J. P., Jain, S., Arora, S. and Singh, U. P., "Vision-Based Gait Recognition: A Survey", in IEEE Access, vol. 6, pp. 70497-70527, 2018.

[11] Birdal, R. G., Sertbaş, A. and Mïhendisliği, B., "Human Identification Based on Gait Analysis: A survey", 2018 3rd International Conference on Computer Science and Engineering (UBMK), Sarajevo, pp. 489-493, 2018.

[12] Ryu, H. T., Lee, C. H., Yoon, H. S. and Yi, B., "Smart staff design to assist walking of elders", 2016 13th International Conference on Ubiquitous Robots and Ambient Intelligence (URAI), Xi'an, pp. 515-518, 2016.

[13] Rampp, A., "Inertial sensor-based stride parameter calculation from gait sequences in geriatric patients", IEEE Trans. Biomed. Engineering, vol. 62, no. 4, pp. 1089-1097, 2015.

[14] Zhao W., Lu H. and Wang D., "Multisensor Image Fusion and Enhancement in Spectral Total Variation Domain", in IEEE Transactions on Multimedia, vol. 20, no. 4, pp. 866-879, 2018.

[15] Lu, H. M., "Motor Anomaly Detection for Unmanned Aerial Vehicles Using Reinforcement Learning", IEEE Internet of Things Journal, vol. 5, no. 4, pp. 2315-2322, 2018.

[16] Yang, X., "Dynamics and Isotropic Control of Parallel Mechanisms for Vibration Isolation", in IEEE/ASME Transactions on Mechatronics, vol. 25, no. 4, pp. 2027-2034, 2020.

[17] Lu H., Zhang M., Xu X., Li Y. and Shen H. T., "Deep Fuzzy Hashing Network for Efficient Image Retrieval", in IEEE Transactions on Fuzzy Systems, vol. 29, no. 1, pp. 166-176, 2021.