

Time-Frequency Feature Analysis of Human Motion Attitude in IMU-based Pedestrian Dead Reckoning

Jiang Yan, Yiming Zhang, Siting Zhou, Qikui Han

School of Electrical Engineering, North China University of Science and Technology, Tangshan, 063200, China

Abstract

Aiming at the core bottlenecks restricting the improvement of positioning accuracy in existing Pedestrian Dead Reckoning (PDR) systems, including the separation between positioning parameter solution and human attitude recognition, the failure to establish a quantitative relationship between attitude features and positioning errors, and the imperfection of the PDR-oriented attitude feature system, this study carries out a time-frequency feature analysis of human motion attitude based on the Inertial Measurement Unit (IMU). In this research, three high-performance IMUs were used to collect triaxial acceleration and angular velocity data of six typical human motions with the sensor mounted on the chest. On this basis, sliding window filtering was determined as the optimal preprocessing scheme with its parameters optimized, a comprehensive time-frequency domain feature system was constructed, and the characteristics of the feature set were verified through multi-subject experiments. The results show that the proposed feature set can clearly distinguish different motion types and reveal the correlation law of time-frequency features of the six typical attitudes. This work provides technical support for high-precision PDR positioning, and has important reference value for the application of self-contained positioning with wearable inertial sensing technology.

Keywords

Human Attitude Recognition; Pedestrian Dead Reckoning; Inertial Measurement Unit; Feature Extraction; Attitude Recognition; Time-Frequency Domain Analysis.

1. Introduction

The global indoor positioning and navigation market has achieved a compound annual growth rate (CAGR) of 23%. As a core positioning technology independent of external signals, Pedestrian Dead Reckoning (PDR) has exceeded a 40% penetration rate in scenarios including emergency rescue and smart wearables [1], serving as a critical technical foundation for autonomous indoor positioning. The deep integration of PDR and Inertial Measurement Unit (IMU) addresses the positioning challenge in environments with obstructed satellite signals, establishes an integrated acquisition chain linking motion attitude to position information, and demonstrates significant interdisciplinary value [2]. With the inherent advantages of compact size, low power consumption, and strong anti-interference capability, IMU has become the core carrier for human motion data acquisition in PDR systems. Correlation analysis between human motion attitude and PDR positioning parameters directly determines the positioning accuracy and robustness, and is the key enabler for advancing the engineering deployment of indoor positioning technologies.

In recent years, the integrated application of IMU and PDR has emerged as a hot topic in interdisciplinary research. In terms of inertial navigation algorithm optimization, Shen et al. [3] proposed a navigation method based on a time-frequency feature encoding neural network, which improved positioning accuracy in complex motion scenarios. However, this work failed to establish

the intrinsic correlation between attitude features and core PDR parameters, and thus could not achieve error compensation at the attitude level. Yi et al. [1] systematically reviewed deep learning methods for IMU-based human motion intention recognition, yet did not explore the quantitative relationship between attitude features and positioning errors. In the field of core PDR parameter optimization, Wan et al. [4] proposed a motion segmentation and heading angle correction algorithm, and Di et al. [5] designed a step length optimization model integrating filtering and neural network, both of which achieved improved positioning accuracy. Nevertheless, neither study considered the impact of different motion attitudes on IMU measurement errors, nor clarified the transmission mechanism of positioning drift induced by attitude calculation errors.

In terms of human attitude recognition, Wei [6] improved action recognition accuracy to 92.1%. However, the proposed feature set has dimensional redundancy and is not screened for PDR scenarios. The multi-position PDR algorithm proposed by Zhang et al. [7] realized multi-position state recognition, but relies on multi-node sensor deployment with inherent limitations in battery life and portability. Chen [8] and Li [9] improved attitude calculation accuracy through multi-sensor fusion, but their studies mostly focused on medical health scenarios, and the feature design is not aligned with the requirements of PDR error compensation. Wang [10] and Sun [2] realized motion pattern recognition based on wrist-worn IMU, but are constrained by the wearing position, making it difficult to accurately capture the overall attitude features of the trunk. Zhang et al. [11] systematically reviewed the key technologies of IMU-based human motion tracking, but did not clarify the quantitative correlation between attitude features and PDR positioning accuracy. In addition, Figo et al. [12] verified the critical role of time-frequency domain feature extraction in motion information analysis [4], providing methodological support for improving the reliability of IMU data.

Critical bottlenecks still exist in existing studies: most studies conduct PDR parameter calculation and attitude recognition separately, failing to establish a quantitative relationship between attitude features and positioning errors; the transmission mechanism of positioning drift caused by attitude calculation errors and sensor noise remains unclear; multi-sensor schemes have inherent limitations in portability and battery life, while single-sensor studies struggle to balance practicability and recognition accuracy; most existing attitude feature sets are not designed for PDR scenarios, and their category discrimination capability remains to be verified.

Aiming at the above limitations, this study focuses on the core requirement of high-precision positioning. Three high-performance IMUs fixed on the chest are employed to collect inertial data of six typical human motions, a comprehensive time-frequency domain feature system is constructed, and the time-frequency feature laws of typical motions are explored through multi-subject experiments. The findings are expected to provide technical support for attitude recognition and error compensation of high-precision PDR systems.

2. Experimental Scheme and Data Acquisition & Processing

2.1 Overall Experimental Design Rationale

This experiment developed a standardized experimental scheme with "data acquisition - preprocessing - feature extraction - result analysis" as the core logic, targeting the requirement of attitude recognition in PDR positioning. The overall design rationale is as follows: healthy adult volunteers were selected as experimental subjects, and high-performance IMUs were fixed on the human chest (placed upright on the anterior chest, a position that can effectively reflect the attitude changes of the human trunk) to collect three-axis acceleration and angular velocity data of a series of motions, including squatting, periodic stepping, running, backward walking, fast walking, and slow walking.

Invalid samples were eliminated through data clipping. Combined features in the time and frequency domains were selected to explore the differences in signal characteristics under different attitudes. Finally, the attitude discrimination capability of the proposed features was verified through experiments, providing technical support for PDR positioning [13]. The core innovations of the

experimental design are the development of personalized preprocessing strategies for different motion types, and the construction of a feature system with complementary time and frequency domain characteristics, so as to improve the accuracy of attitude recognition.

2.2 Experimental Subjects and Equipment

2.2.1 Experimental Subjects and Test Site

To ensure the accuracy of the experimental data, four subjects were recruited for data acquisition. To guarantee the comprehensiveness of the data, the recruited subjects included students and teachers, with a male-to-female ratio of 3:1. The subjects had a body weight ranging from 49 kg to 85 kg and an age ranging from 20 years to 25 years, which eliminated the interference caused by differences in age, height, body weight, and gender. Most of the subjects came from different regions, which further ruled out the influence of regional differences, thus endowing the model constructed with the collected data with better generalizability.

Fig. 1 shows the scene of experimental data acquisition. The test was conducted in an indoor straight site with minimal pedestrian traffic, which provided favorable conditions for data acquisition. The test site was a straight, uniformly flat path, which eliminated the interference caused by significant ground undulation.



Fig.1 Corridor of the Teaching Building

2.2.2 Experimental Equipment

In this experiment, three high-performance Inertial Measurement Unit (IMU) sensors were selected as the core data acquisition equipment, namely the WT901SDCL-BT50 and WT9011DCL-BT50 sensors manufactured by WitMotion, and the IM900 sensor produced by Chenyi Electronic Technology. All three devices feature high measurement accuracy and a wide measurement range. The measurement precision of angle, acceleration, and angular velocity meets the requirement of capturing subtle changes in human body attitude, and the measurement range fully covers the physical quantity variation of typical motions including fast walking, running, and squatting, thus ensuring the integrity and accuracy of raw data.

Furthermore, the three devices are equipped with flexible data transmission modes: wireless Bluetooth transmission is optimized for data acquisition in outdoor and mobile scenarios, while wired TTL transmission guarantees the stability of data transmission during complex motions and eliminates data loss. By conducting synchronous experiments with three devices from different manufacturers and with different accuracy levels, the influence of systematic errors inherent to a single device on experimental results can be effectively mitigated. Meanwhile, this setup verifies the adaptability of the proposed feature set across different devices, thus improving the reliability of the research method.

2.3 Raw Data Acquisition

2.3.1 Types of Human Motions

In line with the practical application requirements of PDR positioning in indoor and outdoor scenarios, and with comprehensive consideration of the typicality, periodicity, and attitude differentiation of human motions, this study selected six representative types of human motions as research objects, covering periodic motions, linear motions, and non-periodic motions. These motions fully cover the core motion patterns in daily travel and special scenarios, providing diversified data support for attitude recognition model training and PDR positioning error compensation. The specific definitions and standardized parameters of each motion type are presented in Table 1.

Table 1. Motion Plan

Motion Type	Motion Description
In-situ Stepping	Alternately lift and lower the feet for 60 repetitions
Running	Run forward at a constant speed for 100 m
Fast Walking	Walk forward at a relatively fast speed for 100 m
Slow Walking	Walk forward at a relatively slow speed for 100 m
Backward Walking	Walk backward (consistent with the forward walking test distance in formal experiments)
Squatting	Keep both feet stationary, and complete 10 repetitions of full standing-squatting cycles

The above six types of motions were selected based on three core considerations: first, the selected motions have comprehensive coverage, including daily high-frequency linear motions, non-displacement motions, and special-scenario motions such as backward walking, which can simulate the diversified application scenarios of PDR positioning [1]; second, the selected motions have significantly distinct characteristic signatures, which can provide sufficient discriminability for feature extraction and classification; third, the motions have a high degree of standardization with clear execution parameters defined, which can avoid data dispersion caused by non-standard motion execution, ensure the consistency and comparability of the collected data, and lay a reliable foundation for subsequent research [13].

2.3.2 Experimental Procedure

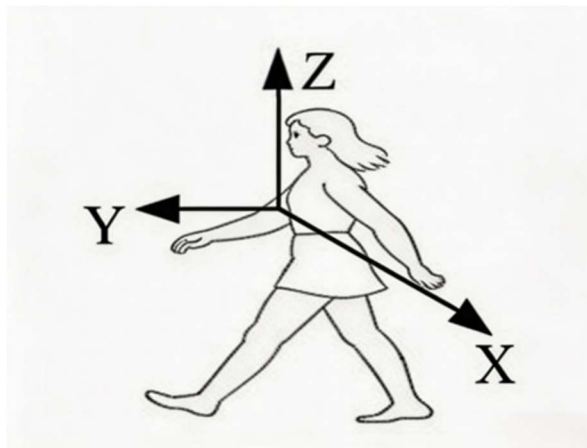


Fig.2 Wearing Position and Orientation of the IMU Sensor

The IMU sensor was fixed on the anterior chest of the subject, with its X-axis parallel to the ground, Y-axis pointing to the forward direction of human motion, and Z-axis perpendicular to the ground (as shown in Fig. 2). Calibration of acceleration and angular velocity was performed to eliminate zero drift and environmental interference. The sampling rate of the sensor was set to 50 Hz [2], and the sensor was synchronously connected to the mobile acquisition device via Bluetooth. The subjects completed a sequence of typical motions for PDR positioning including standing, walking, and squatting, with each motion repeated 3 times and each single trial lasting 20–50 seconds. The acquired data were stored in TXT format with dual backup.

2.3.3 Description of Raw IMU Data Acquisition

The raw IMU data were stored in TXT format with dual backup to ensure data security and integrity. The core data fields include millisecond-level timestamps, three-axis acceleration, three-axis angular velocity, and digitally encoded motion labels, which are used for time sequence correlation and category labeling, respectively. The sampling rate was set to 50 Hz, which meets the requirement for capturing human motion signals with a maximum effective frequency of 20 Hz. This setup enables complete capture of motion details and signal patterns, providing high-quality raw data for subsequent research.

2.4 Dataset Construction

2.4.1 Raw Data Clipping Rules

The raw IMU data were acquired using MEMS-IMU sensors as the core acquisition equipment, with a sampling frequency set to 50 Hz. This setup enables complete capture of the dynamic variation characteristics of acceleration and angular velocity during human motion, providing raw data support for subsequent analysis. To avoid interference from non-stationary data at the start and end of each motion, the transition segments in the initiation and termination phases of each motion execution were eliminated, and only the data from the middle 10 seconds of stable motion execution were selected as the core analysis samples. Meanwhile, the acceleration modulus was adopted as the key criterion to determine the starting point of sample clipping, which effectively avoids fluctuation interference in the motion initiation phase, ensures uniform initial conditions for all samples, and lays a standardized data foundation for feature comparison across different motions.

2.4.2 Dataset Construction

To fully reflect the dynamic characteristics of human motion and lay a foundation for the subsequent extraction of time-domain and frequency-domain features, preliminary processing was performed on the three-axis acceleration and angular velocity to generate the acceleration modulus and angular velocity modulus, which can comprehensively characterize the features of three-axis acceleration and angular velocity. Their definitions are as follows:

The acceleration modulus is a comprehensive representation of the data acquired by the three-axis acceleration sensor of the Inertial Measurement Unit (IMU), which is used to reflect the intensity and variation trend of acceleration during human motion. It is defined based on the three-axis acceleration components in the three-dimensional Cartesian coordinate system and calculated via vector synthesis. The specific expression is shown in Equation 1:

$$a_{\text{mag}} = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (1)$$

Where a_x , a_y , and a_z are the instantaneous acceleration values acquired by the IMU along the x, y, and z coordinate axes, respectively.

The angular velocity modulus is used to describe the intensity of rotational motion during human movement. It is also calculated via vector synthesis based on the data collected by the three-axis angular velocity sensor, with the specific expression shown in Equation 2:

$$\omega_{\text{mag}} = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2} \quad (2)$$

where ω_x , ω_y , and ω_z are the instantaneous angular velocity values acquired by the IMU along the x, y, and z coordinate axes, respectively.

The final constructed sample set covers six types of human motions. In this experiment, the data were stored by motion type, which not only takes into account the diversity of motion types but also ensures the standardization characteristics of the data, providing reliable fundamental data support for subsequent research work.

3. Feature Selection of IMU Measurement Indicators

3.1 Selection of Time-Domain Feature Indicators

3.1.1 Mean Acceleration

Mean acceleration is a fundamental time-domain indicator that describes the overall variation trend of IMU acceleration signals. The core value of this indicator lies in capturing the difference in the baseline level of acceleration signals under different motion attitudes. It is calculated based on the arithmetic mean of the acceleration modulus of all sampling points, which can effectively filter out the interference of transient impulse noise on feature characterization, with the advantages of simple calculation and clear physical significance. It is complementary to indicators reflecting dispersion characteristics such as acceleration variance and interquartile range, providing fundamental support for the accurate differentiation of different human body attitudes and a basic reference for subsequent complex feature analysis [12]. For human motion, the higher the motion intensity and the more dramatic the dynamic change of attitude, the higher the mean acceleration generally is. The calculation formula of mean acceleration is shown in Equation 3:

$$\bar{a} = \frac{1}{N} \sum_{i=1}^N a_i \quad (3)$$

where \bar{a} is the mean acceleration, N is the number of sampling points of the acceleration signal, and a_i is the acceleration modulus of the i -th sampling point.

3.1.2 Variance of Acceleration

Variance of acceleration is a core time-domain indicator for measuring the dispersion degree of acceleration signals, which can effectively reflect the stability of human motion attitudes. The core function of variance is to quantify the dispersion degree of the IMU acceleration signal and accurately reflect the differences in motion intensity and stability under different human body attitudes. By quantifying the degree of deviation of the acceleration signal from the mean value, this indicator can distinguish the differences in acceleration fluctuations under different motion attitudes. The higher the motion intensity and the more unstable the attitude, the larger the variance of acceleration generally is. The calculation formula of variance is shown in Equation 4:

$$\sigma_a^2 = \frac{1}{N-1} \sum_{i=1}^N (a_i - \bar{a})^2 \quad (4)$$

where N is the number of sampling points of the acceleration signal, a_i is the acceleration modulus of the i -th sampling point, and \bar{a} is the mean value of the acceleration modulus of all sampling points.

3.1.3 Interquartile Range of Acceleration

The interquartile range (IQR) of acceleration is a robust indicator reflecting the dispersion degree of the acceleration signal distribution, which can effectively avoid the interference of outliers on feature characterization. Focusing on the distribution range of the middle 50% of the data, the IQR of acceleration can accurately capture the central tendency of the acceleration signal. It is suitable for feature differentiation under different motion attitudes, and especially has excellent stability in scenarios with data noise. The calculation formula of the interquartile range is shown in Equation 5:

$$IQR_a = Q_3 - Q_1 \quad (5)$$

where Q_1 and Q_3 are the first quartile (25th percentile) and the third quartile (75th percentile) obtained by sorting the acquired acceleration modulus data in ascending order, respectively.

3.1.4 Root Mean Square of Angular Velocity

The root mean square (RMS) of angular velocity is a key indicator characterizing the energy magnitude of the angular velocity signal, which can reflect the intensity of rotational motion of the human body. This indicator can comprehensively reflect the overall energy level of the angular velocity signal. The more intense the rotational motion, the larger the RMS value of angular velocity, which is suitable for distinguishing human motion attitudes with different dynamic characteristics. The calculation formula of the angular velocity RMS is shown in Equation 6:

$$\omega_{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N \omega_i^2} \quad (6)$$

where N is the number of sampling points of the angular velocity signal, and ω_i is the angular velocity modulus of the i -th sampling point.

3.2 Selection of Frequency-Domain Feature Indicators

3.2.1 Spectral Centroid

Spectral centroid is a frequency-domain feature reflecting the center of the signal frequency distribution, which characterizes the concentrated position of signal energy on the frequency axis. Its calculation is based on the spectral centroid formula for discrete signals. This indicator can effectively distinguish the frequency characteristics of different motion attitudes: the higher the motion frequency, the more the spectral centroid shifts to the high-frequency region. Meanwhile, the spectral centroid can distinguish similar motions and enhance the anti-interference performance of the feature system. The calculation formula of the spectral centroid is shown in Equation 7:

$$SC = \frac{\sum_{k=1}^{N/2} f_k \cdot |X[k]|}{\sum_{k=1}^{N/2} |X[k]|} \quad (7)$$

where f_k is the frequency value (Hz) of the k -th frequency component, $|X[k]|$ is the amplitude value of the k -th frequency component, and N is the number of Fast Fourier Transform (FFT) points.

3.2.2 Dominant Frequency

Dominant frequency refers to the frequency value corresponding to the frequency component with the maximum amplitude in the signal spectrum, which is a core frequency-domain indicator characterizing the periodicity of human motion. Its acquisition process is as follows: first, FFT is performed on the time-domain acceleration and angular velocity signals collected by the IMU to obtain the corresponding frequency-domain spectrum; then the frequency component with the maximum amplitude in the spectrum is identified, and the frequency corresponding to this component is the dominant frequency. Different human motion attitudes have unique motion cycles with significant differences in dominant frequency: motion attitudes with strong periodicity have relatively concentrated dominant frequency, while motion attitudes with complex dynamic changes have more distinct dominant frequency characteristics. Thus, the dominant frequency can effectively realize the differentiation of different motion attitudes. The calculation formula of the dominant frequency is shown in Equation 8:

$$f_d = \frac{\arg \max_{k \in [0, N-1]} \frac{1}{N} |X(k)|^2 \cdot f_s}{N} \quad (8)$$

where N is the signal length, $X(k)$ is the complex spectrum value of the k -th frequency point, and f_s is the sampling frequency.

3.3 Rationality and Comparative Explanation of Feature Selection

The time-domain and frequency-domain feature indicators selected in this study all have clear physical significance and specific targeting for PDR scenarios, which can fully cover the dynamic characteristics of human motion. In the time domain, the mean acceleration intuitively reflects the baseline intensity of motion; the variance and interquartile range of acceleration characterize the acceleration signal features from the perspectives of overall dispersion and robust dispersion, respectively; the RMS of angular velocity reflects the intensity of human rotational motion. These four indicators are complementary to each other from the four dimensions of "average level - overall dispersion - robust dispersion - rotational energy", and fully capture the dynamic characteristics of human linear motion and rotation [10]. In the frequency domain, the spectral centroid reflects the concentrated position of the signal frequency distribution, and the dominant frequency reflects the dominant cycle of motion. The combination of the two can accurately capture the differences in frequency characteristics of different motion attitudes.

The features selected in this study have both excellent discrimination and stability. After filtering preprocessing, they can effectively suppress data noise and avoid feature redundancy. Compared with single-dimensional features, the multi-domain time-frequency fusion feature system can comprehensively utilize the time-domain dynamic intensity information and frequency-domain periodicity information to fully characterize the essential characteristics of human motion attitudes [14]. It provides reliable feature support for the subsequent construction of attitude recognition models and PDR positioning error compensation, and guarantees the practical application value of the feature set.

4. Conclusion

4.1 Feature Analysis of Motions based on Multiple Sets of Experimental Data

4.1.1 Time-Domain Analysis of Motion Features from Multiple Sets of Experimental Data

Time-domain features can directly reflect the amplitude and stability of inertial signals during human motion. Through key statistical indicators of acceleration and angular velocity, they can clearly reveal the essential differences in motion intensity and signal stability between different motions, providing

a critical basis for attitude recognition. Fig. 3 shows the acceleration and angular velocity characteristics of different motions from multiple subjects [15][16].

The mean acceleration can intuitively reflect the difference in inertial force under different motion intensities, with impulsive high-intensity motions showing significantly higher values than low-intensity stable motions. The variance of acceleration reflects the intensity of signal fluctuation, with values of impulsive motions much larger than those of periodic walking motions. The interquartile range of acceleration can reflect the distribution characteristics of the signal and assist in distinguishing the periodicity and impulsiveness of motions. The combination of these three indicators can effectively classify motion patterns and provide quantitative support for motion differentiation.

The RMS of angular velocity can clearly reflect the intensity of attitude changes during motions. Motions with large-scale attitude adjustment such as squatting have significantly higher values, while stable translational motions such as slow walking are in a lower range. High-frequency swinging motions such as in-situ stepping also have significantly higher values than conventional walking. This indicator can accurately distinguish motions with dramatic attitude changes and stable translational motions, and plays a key role in the recognition of complex motions.

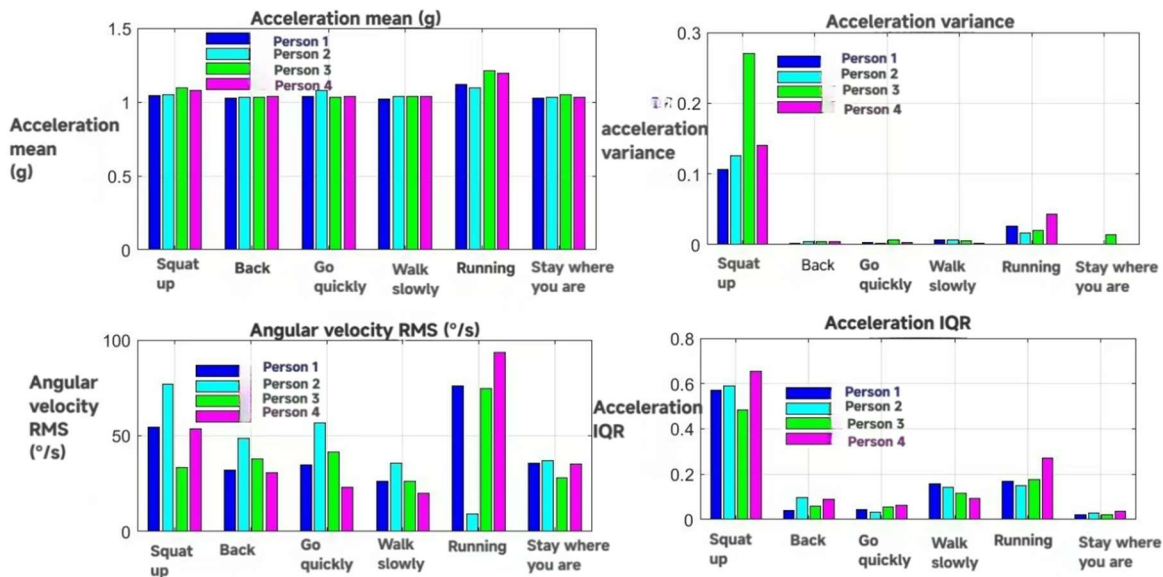


Fig.3 Statistical Graph of Time-Domain Features for Different Human Motions

4.1.2 Frequency-Domain Analysis of Motion Features from Multiple Sets of Experimental Data

Frequency-domain features can effectively characterize the rhythmicity and frequency distribution law of human motion. Through the analysis of the dominant frequency and spectral centroid of acceleration and angular velocity signals, they can accurately distinguish different motion attitudes, providing a fundamental basis for action recognition and positioning error compensation.

Based on the dominant frequency distribution of each motion for different subjects in Fig. 4 and Fig. 5, this study finds that the dominant frequencies of different motions present a clear gradient distribution due to differences in motion characteristics. Specifically, motions with strong periodicity and high motion frequency have overall high dominant frequency values, while motions with gentle dynamic changes and long motion cycles have low dominant frequency values. For the same motion, the dominant frequency distributions of the four subjects are highly consistent, with only minor individual differences. Such differences do not alter the overall hierarchy and distribution trend of the dominant frequency for the corresponding motion, which fully demonstrates the population-level generalizability of the motion dominant frequency feature. Meanwhile, the ranking trends of the dominant frequencies of angular velocity and acceleration for different motions are highly

synergistic. Both indicators can jointly reflect the motion frequency characteristics of the actions, and the inherent motion characteristics of the action are the core factor determining its dominant frequency level.

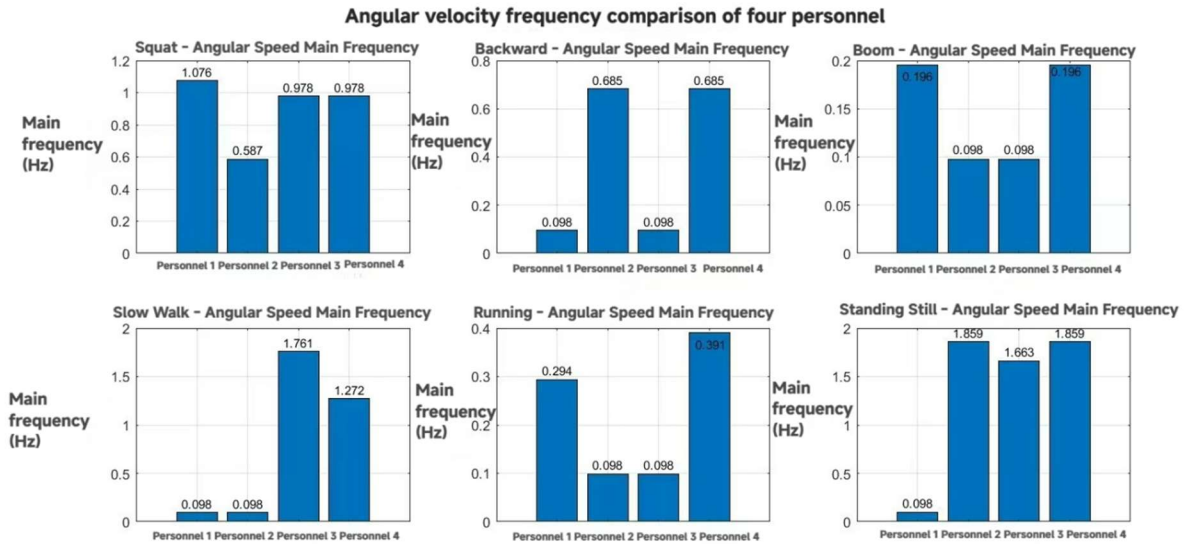


Fig.4 Dominant Frequency Distribution of Angular Velocity for Each Motion Type Among Different Subjects

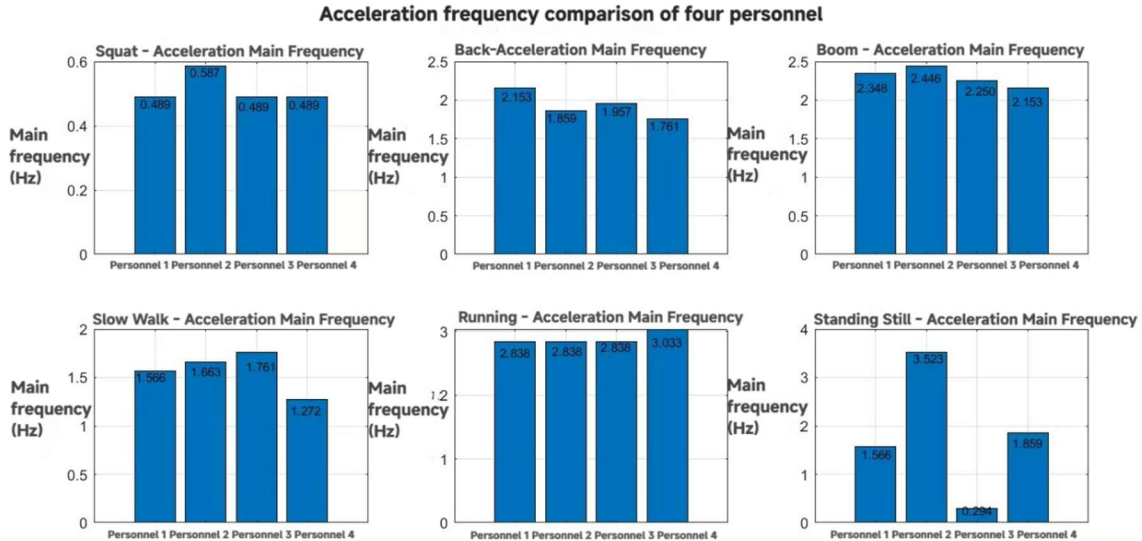


Fig.5 Dominant Frequency Distribution of Acceleration for Each Motion Type Among Different Subjects

The spectral centroid describes the energy distribution center of the signal spectrum. It can effectively distinguish motion patterns with similar intensity, and exhibits significant sensitivity to both motion intensity and motion patterns. This enables it to accurately subdivide the motion characteristics of similar actions, thus providing a more refined frequency-domain discrimination basis for attitude recognition.

Based on the distribution of the spectral centroid of each motion for different subjects in Fig. 6 and Fig. 7, this study finds that the spectral centroids of different motions present significant gradient

differentiation characteristics. Specifically, motions with strong periodicity and high motion frequency have overall high spectral centroid values, while motions with gentle dynamic changes and long motion cycles have low spectral centroid values. For the same motion, the variation trends of the spectral centroid of the four subjects are highly consistent, with only local differences among individuals. More importantly, such differences do not alter the overall hierarchy and distribution pattern of the spectral centroid for the corresponding motion, which fully demonstrates the population-level stability of the spectral centroid feature. Meanwhile, although the spectral centroids of angular velocity and acceleration show slight differences in local distribution, the ranking trends of the spectral centroids for different motions are highly synergistic. Both indicators can effectively reflect the motion frequency characteristics of the actions, and the inherent motion characteristics of the action are still the core factor determining its spectral centroid level.

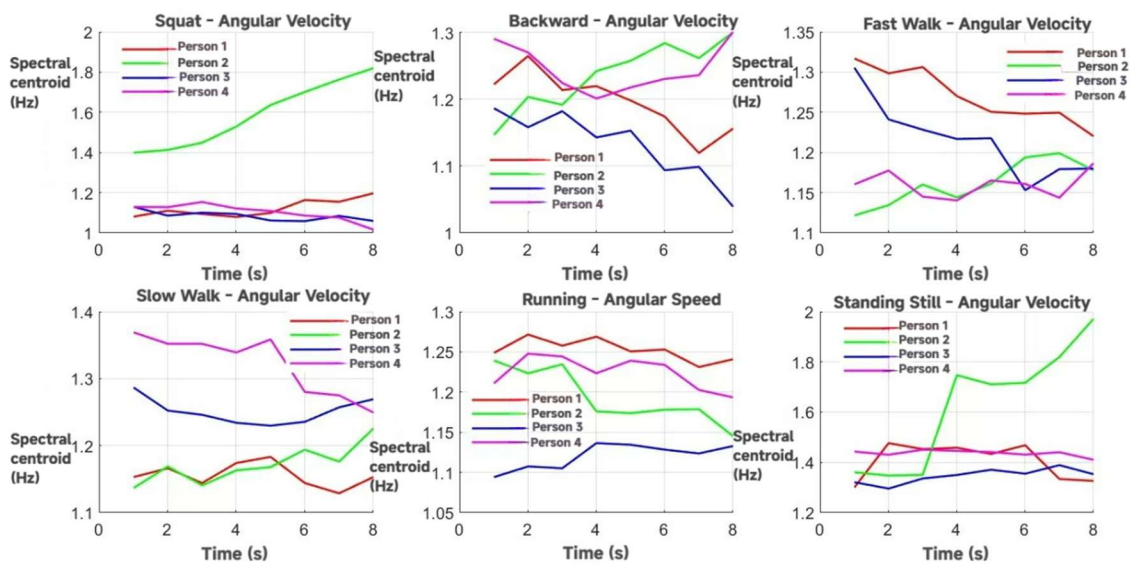


Fig.6 Spectral Centroid Distribution of Angular Velocity for Each Motion Type Among Different Subjects

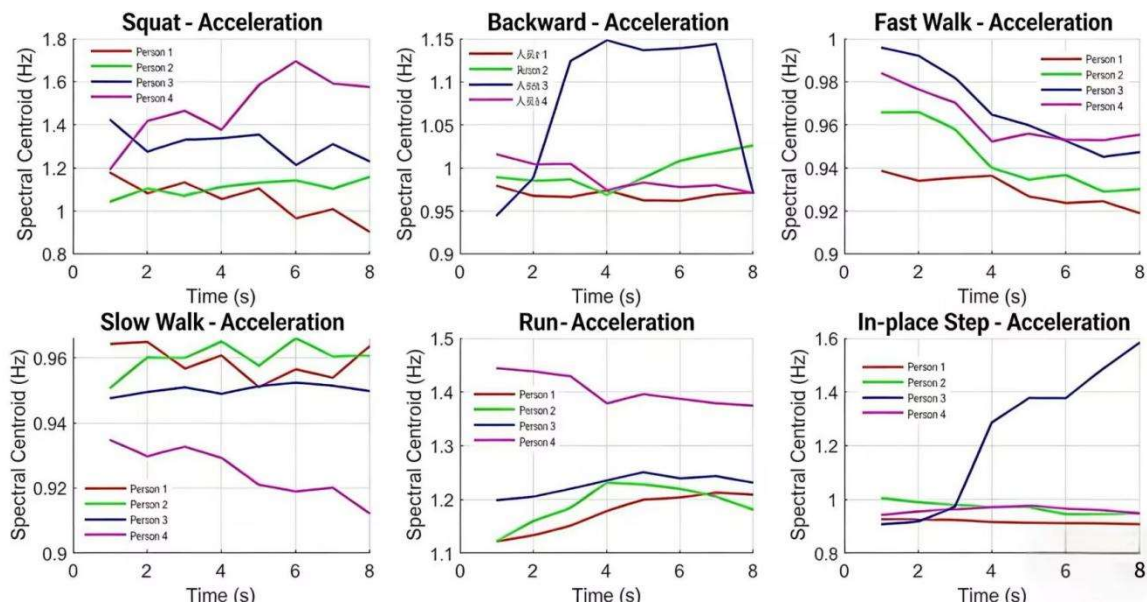


Fig.7 Spectral Centroid Distribution of Acceleration for Each Motion Type Among Different Subjects

5. Summary of Work

To address the core requirement of the strong correlation between human motion attitude recognition, positioning accuracy and robustness in Pedestrian Dead Reckoning (PDR) systems, as well as the limitations of existing studies including insufficient systematic analysis between attitude features and PDR positioning parameters and inadequate generalizability of features, this study takes the Inertial Measurement Unit (IMU) as the core to conduct research on time-frequency features of human motion attitudes adapted to PDR positioning. Herein, four subjects were recruited, and three IMU sensors were used to collect three-axis acceleration and angular velocity data of six typical human motions from the chest, based on which a comprehensive feature system covering time-domain and frequency-domain indicators was constructed. The results demonstrate that the proposed feature set has strong category discrimination capability and excellent robustness. It can clearly distinguish different types of motions, reveal the correlation laws of time-frequency features of the six typical attitudes, and provide reliable quantitative support for motion pattern classification and action recognition.

References

- [1] YI Chunzhi, JIA Yicheng, JIANG Feng, and WANG Xiulai, "Inertial measurement unit based human motion intention recognition methods: Status and challenges," *CAAI Transactions on Intelligent Systems*, vol.20, no.4, pp.763–775, 2025.
- [2] SUN Xiang, "Design and implementation of wearable human behavior recognition system based on IMU," Master's Thesis, Nanjing University of Information Science & Technology, Nanjing, Jiangsu, China, 2017.
- [3] SHEN Dehan and CHEN Changhao, "Pedestrian inertial navigation method based on time-frequency feature encoding neural network," *Navigation and Control*, vol.24, no.6, pp.84–93, 2025.
- [4] WAN Pengbo, LI Xueqing, and TANG Yunqi, "Research on an improved pedestrian dead reckoning algorithm," *Electronic Measurement Technology*, vol.47, no.11, pp.69–77, 2024.
- [5] DI Ke, LIU Jiabin, DU Jijia, REN Jie, ZHAO Weifeng, and LIU Yu, "Improved research on step length estimation model of PDR algorithm," *Journal of Electronic Measurement and Instrumentation*, vol.36, no.11, pp.178–185, 2022.
- [6] WEI Xuanxuan, "Human attitude recognition algorithm based on inertial sensors," *Intelligent Computer and Applications*, vol.12, no.6, pp.97–101, 105, 2022.
- [7] ZHANG Xiaohong, LUO Kegan, TAO Xianlu, HU Xin, and LIU Wanke, "A multi-position PDR algorithm based on state recognition of wearable MEMS sensors," *Geomatics and Information Science of Wuhan University*, vol.46, no.12, pp.1791–1801, 2021.
- [8] CHEN Jialong, "Human pose detection and implementation based on multi-modal information fusion," Master's Thesis, Heilongjiang University, Harbin, Heilongjiang, China, 2021.
- [9] LI Jinghui, "Research on human attitude recognition based on multi-sensor information fusion," Master's Thesis, Shandong University, Jinan, Shandong, China, 2014.
- [10] WANG De, "Research on human motion pattern and personal identity recognition algorithm based on IMU," Master's Thesis, Ningxia University, Yinchuan, Ningxia, China, 2020.
- [11] ZHANG Yunhao, HE Baiyue, YANG Xusheng, and ZHANG Wenan, "A review of human motion tracking methods based on wearable inertial sensors," *Acta Automatica Sinica*, vol.45, no.8, pp.1439–1454, 2019.
- [12] D.Figo, P.C.Diniz, D.R.Ferreira, and J.M.Cardoso, "Preprocessing techniques for context recognition from accelerometer data," *Personal and Ubiquitous Computing*, vol.14, no.7, pp.645–662, 2010.
- [13] YIN Xiaoling, CHEN Xiaojiang, XIA Qishou, et al., "Human motion state recognition based on built-in sensors of smart phones," *Journal on Communications*, vol.40, no.3, pp.157–169, 2019.
- [14] SUN Wei, SONG Ruyi, and DING Wei, "Adaptive discrimination of gait feature extraction based on K-means clustering," *Science of Surveying and Mapping*, vol.44, no.12, pp.29–34, 2019.
- [15] CHEN Peng, LIAO Ming, LIU Wuping, et al., "Analysis and application of key technologies for indoor positioning integrating trilateration and PDR," *Bulletin of Surveying and Mapping*, no.2, pp.17–21, 2019.

- [16]XU Yongtao,“Research on human attitude recognition and trajectory reconstruction method based on inertial sensors,” Master’s Thesis,Southeast University,Nanjing,Jiangsu,China,2022.