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Design of a Real-Time Interactive System for Dance Motion Feature Extraction Based on Flexible Textile Sensor Networks

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ABSTRACT Traditional dance motion capture systems suffer from limited wearability, insufficient motion feature extraction accuracy, and delayed real-time interaction, posing challenges for intelligent wearable sensing and wireless information acquisition. To address these issues, this study proposes a real-time interactive framework for dance motion feature extraction based on a flexible textile sensor network, with potential relevance to low-power wearable sensing and electromagnetic-assisted wireless monitoring technologies. A wearable sensing architecture integrating flexible pressure sensors and inertial measurement units (IMUs) is constructed and deployed at key human joints to achieve unconstrained acquisition of multidimensional motion information. A multi-source data fusion preprocessing strategy combining Kalman filtering and sliding-window temporal alignment is introduced to improve signal quality and synchronization. Subsequently, a Bi-GRU-Attention model is developed to extract dynamic features including joint trajectories, angular velocity, and acceleration, while a motion feature library covering classical, modern, and street dance is established. Furthermore, an integrated real-time interaction system incorporating data acquisition, feature extraction, wireless transmission, and interactive feedback is implemented, where extracted motion features are compared with predefined standard actions to generate visual guidance and haptic feedback. The proposed framework provides an effective solution for intelligent wearable motion analysis and offers valuable references for flexible sensing, wireless signal processing, and real-time interactive systems in advanced engineering applications.

INDEX TERMS flexible textile sensor networks, dance motion feature extraction, Bi-GRU-Attention, wireless sensing, multi-source data fusion

I. INTRODUCTION

A. RESEARCH BACKGROUND

As the core medium of physical art, dance's quality of performance and teaching effectiveness are directly determined by the standardization, coordination, and precision of emotional expression in its movements [1]. Traditional dance instruction relies on verbal instruction and visual observation, leading to significant subjective evaluation biases and difficulties in quantifying movement details. In stage performances and choreography, the absence of real-time motion capture and interactive feedback mechanisms limits innovation in artistic expression [2]. With advancements in intelligent sensing, deep learning, and human-computer interaction technologies, wearable motion capture systems have emerged as a key solution to these challenges.

However, existing dance motion capture technologies face significant limitations: optical capture systems are costly and location-dependent, failing to meet routine teaching and outdoor performance needs; rigid sensors offer poor comfort, constrain limb movement, and hinder natural dance expression; and single-sensor data lacks sufficient feature extraction capability, making it difficult to accurately capture the dynamic changes of complex dance movements while causing real-time interactive response delays [3]. Flexible textile sensing technology, with its advantages of softness, breathability, body-hugging fit, and high wearability, offers new possibilities for non-intrusive motion capture [4]. Integrating this technology with deep learning algorithms to build a dance motion feature extraction and real-time interaction system enables both precise motion data acquisition and quantitative analysis, while providing real-time feedback guidance. This holds significant theoretical value and engineering application implications for enhancing dance teaching efficiency, enriching artistic creation forms, and advancing the intelligent development of dance art.

B. CURRENT RESEARCH STATUS DOMESTICALLY AND ABROAD

Overseas research in flexible textile sensing began earlier and has reached greater maturity. The Georgia Tech team in the United States developed a flexible textile pressure sensor based on carbon nanotubes, achieving a sensitivity of 1.2 kPa^{-1} and enabling the perception of subtle limb movements [5]. Germany's Fraunhofer Institute developed smart dancewear integrating an IMU with flexible strain sensors, capable of collecting joint angle and motion trajectory data [6]. However, most international products focus on collecting single motion parameters, lacking multi-source data fusion and optimization for extracting specific dance motion features [7-10].

C. RESEARCH CONTENT

1. Flexible Textile Sensor Network Design: Develop flexible pressure-inertia composite sensor nodes and optimize sensor network layout to achieve non-intrusive collection of multi-dimensional dance motion data;

2. Multi-source sensor data preprocessing and fusion: Design Kalman filtering and sliding window time alignment algorithms to suppress noise interference and enhance data reliability;

3. Dance movement feature extraction model construction: Propose a Bi-GRU-Attention model to capture temporal dynamic features and joint coordination characteristics of movements, building a multi-dance genre feature library;

4. Real-time interactive system construction: Design wireless communication modules, feature comparison modules, and multimodal feedback modules to achieve integrated "collection-extraction-feedback" interaction.

II. THEORETICAL FOUNDATIONS

A. PRINCIPLES OF FLEXIBLE TEXTILE SENSING TECHNOLOGY

1) Sensor Node Types and Characteristics

The system employs flexible pressure sensors and inertial measurement units (IMUs) to construct composite sensing nodes. The core characteristics of both sensor types are illustrated in Figure 1.

Flexible pressure sensors utilize a conductive yarn weave structure. When limb movement causes sensor deformation, the resistance of the conductive pathways changes, enabling pressure sensing through resistive signal conversion. The IMU integrates a three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer, providing real-time output of human joint motion posture and kinematic parameters [11].

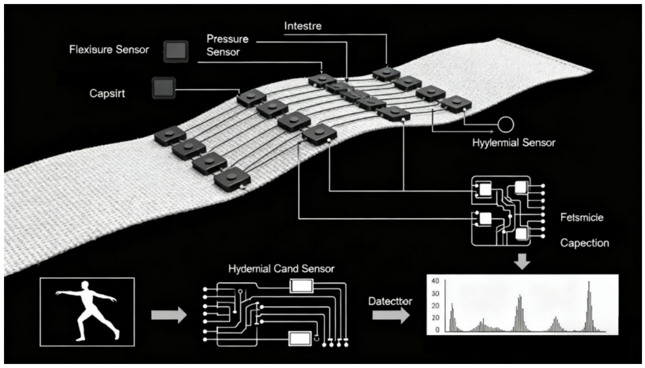

FIGURE 1. Principles of Flexible Textile Sensing Technology

2) Sensor Network Deployment Principles

Sensor node deployment must ensure comprehensive coverage and interference-free operation for dance motion capture, adhering to the following principles:

1. Key Position Coverage: Deploy sensors on nine key positions—shoulder, elbow, wrist, hip, knee, ankle, midthoracic spine, thumb tip, and toe base;

2. Force-Sensitive Zone Alignment: Position pressure sensors at joint force points and IMUs along joint midlines to enhance measurement accuracy;

3. Non-intrusive Design: Sensing nodes are encapsulated in flexible textile materials, with thickness <2mm and weight <5g, to avoid impacting natural dance expression.

B. MULTI-SOURCE DATA FUSION TECHNOLOGY

'Multi-source' refers to the diversity of data sources, specifically including two distinct types of sensing nodes: pressure sensors and IMUs; 'multi-dimensional' denotes the diversity of data representations, specifically encompassing kinematic dimensions (joint angles, angular velocities, accelerations), mechanical dimensions (pressure peaks, averages, rates of change), and temporal dimensions (action duration, phase characteristics).

1. Kalman Filtering: Suppresses random noise in IMU data. The core formula is as follows:

$$x^k = Ax^{k-1} + Bu^{k-1} + K_k(z_k - Hx^{k-1}) \tag{1}$$

2. Sliding Window Timing Alignment: Employing a 50ms sliding window to synchronize pressure sensor and IMU data, ensuring temporal consistency across multi-source data [12].

Feature-level fusion integrates multi-source sensor data through the following process: First, extract force features (peak, mean, variance) from the pressure sensor and attitude features (joint angles, angular velocity, acceleration) from the IMU. Then, generate a unified feature vector via adaptive weighted fusion using the following formula:

$$F = \alpha F_p + (1 - \alpha)F_i \tag{2}$$

Among these, F represents the fusion feature vector, αF_p denotes the pressure feature, F_i signifies the inertia feature, and α is the adaptive weight (optimized to 0.35 through training) [13].

C. CORE DEEP LEARNING MODELS

1) Gated Recurrent Unit (GRU)

GRU controls information propagation via update and reset gates, effectively addressing gradient vanishing issues in long-term sequence data and proving suitable for action sequence feature extraction. Core equations are as follows:

$$\text{Update gate:}\quad z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{3}$$

$$\text{Reset gate:}\quad r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{4}$$

$$\text{Candidate hidden state:}\quad \widetilde{h}_t = \tanh(W_h x_t + r_t \odot U_h h_{t-1} + b_h) \tag{5}$$

$$\text{Hidden state update:}\quad h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \widetilde{h}_t \tag{6}$$

Where x_t denotes the input feature at time t, h_{t-1} represents the previous hidden state, W, U, and b are trainable parameters, and σ is the Sigmoid activation function [14].

2) Bidirectional Gated Recurrent Unit (Bi-GRU)

Bi-GRU consists of a forward GRU and a backward GRU, enabling simultaneous capture of forward and backward features in temporal data to enhance the ability to capture action-sequence correlations. Its output is the concatenation of bidirectional hidden states:

$$h_t^{bi} = [\overrightarrow{h_t} \| \overleftarrow{h_t}] \tag{7}$$

Among these, ht→ denotes the forward GRU output, and [] represents feature concatenation.

3) Attention Mechanism

The attention mechanism is introduced to weight the temporal features output by the Bi-GRU, thereby enhancing the feature representation of key action segments. The core formula is as follows:

$$\text{Attention score:}\quad e_t = v^T \tanh(W_a h_t^{bi} + b_a) \tag{8}$$

$$\text{Attention Weight:}\quad \alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \tag{9}$$

$$\text{Weighted Feature Output:}\quad F_{att} = \sum_{t=1}^{T} \alpha_t h_t^{bi} \tag{10}$$

Here, v, W_a, b_a are trainable parameters, T denotes the sequence length, and α_t represents the attention weight at time step t.

D. SYSTEM EVALUATION METRICS

1) Feature Extraction Performance Metrics

1. Motion Classification Accuracy: Measures the model's ability to recognize dance action types, calculated as:

$$Accuracy = \frac{N_{correct}}{N_{total}} \times 100\% \tag{11}$$

Among these, $N_{correct}$ denotes the number of correctly classified motion samples, while N_{total} represents the total number of samples.

2) Real-time Performance Metrics

Real-time performance is measured by system response latency, defined as the total duration from sensor data acquisition to interactive feedback output. This includes data transmission delay, feature extraction delay, and feedback generation delay [15].

3) Wear Comfort Metrics

A 10-point rating system was employed, inviting dance professionals to evaluate three dimensions: softness, breathability, and freedom of movement. The average score was taken as the comfort rating [16].

III. FLEXIBLE TEXTILE SENSOR NETWORK AND SYSTEM ARCHITECTURE DESIGN

A. OVERALL SYSTEM ARCHITECTURE

The system adopts a four-layer architecture: "sensing layer – data transmission layer – data processing layer – interactive feedback layer," as shown in Figure 2.

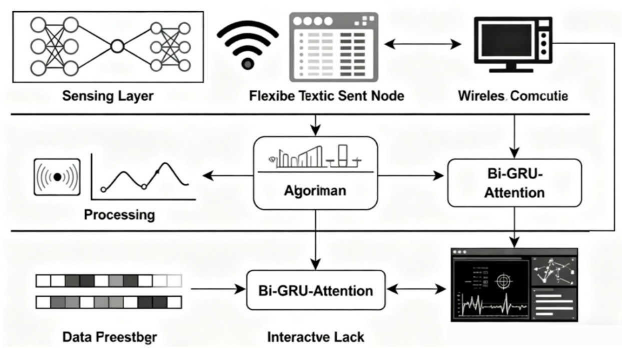

FIGURE 2. Overall System Architecture

The sensing layer collects multi-source motion data through a flexible textile sensor network; the data transmission layer employs dual-mode Bluetooth 5.2 and WiFi communication for real-time data transfer; the data processing layer performs data preprocessing, feature extraction, and motion comparison; the interactive feedback layer outputs real-time guidance feedback via a visual interface and vibration module [17-19].

B. FLEXIBLE TEXTILE SENSOR NETWORK DESIGN

1) Sensor Node Hardware Design

1. Core Component Selection: Flexible pressure sensors employ conductive yarn weaving structures with sensitivity of 1.5 kPa^{-1} and response time <20 ms; the MPU6050 chip serves as the IMU, integrating a triaxial accelerometer and gyroscope with measurement accuracy of $\pm 0.01°$.

2. Signal Conditioning Module: Designed a low-noise amplifier and analog-to-digital converter (ADC) to convert

sensor analog signals into 16-bit digital signals, with a adaptive sampling mechanism (100 Hz for conventional movements, 200 Hz for rapid street dance actions);

3. Packaging Design: Employed flexible silicone encapsulation for encapsulation, with a thickness of 1.2 mm and weight of 3.5 g. The surface utilizes breathable textile fabric to enhance wear comfort [20-22]. Added dynamic power regulation mechanism: sampling rate drops to 50 Hz in idle state; WiFi module automatically sleeps without long-range transmission needs. Average power consumption optimized to 28 mA.

2) Sensor Network Layout

The sensor network comprises nine composite sensing nodes deployed at the following locations with corresponding functions, the details as shown in Table 1:

TABLE 1. Deployment Positions, Sensor Types, and Core Functions of the Flexible Textile Sensor Network

Deployment Position	Sensor Type	Measurement Parameters	Core Function
Lateral Shoulder	Pressure Sensor + IMU	Abduction/Adduction Angle, Movement Force	Capture the movement trajectory of shoulder limbs
Medial Elbow Joint	Pressure Sensor + IMU	Flexion Angle, Extension Force	Monitor the standardization of elbow flexion and extension movements
Medial Wrist	Pressure Sensor + IMU	Rotation Angle, Hand Movement Force	Perceive fine movement changes of the wrist
Lateral Hip	Pressure Sensor + IMU	Opening/Closing Angle, Lower Limb Movement Trajectory	Record the lower limb movement driven by the hip
Posterior Knee Joint	Pressure Sensor + IMU	Flexion Angle, Support Force	Detect knee joint flexion/extension and weight-bearing status
Lateral Ankle	Pressure Sensor + IMU	Flexion/Extension Angle, Balance Status	Ensure balance and stability monitoring of dance movements
Mid-thoracic Spine	Pressure Sensor + IMU	Spinal Flexion/Extension Angle, Rotational Angular Velocity	Capture trunk rotation and spinal flexion/extension movements
Thumb Tip	Pressure Sensor + IMU	Finger Grip Force, Flexion/Extension Angle	Perceive fine finger movements
Toe Base	Pressure Sensor + IMU	Toe Support Force, Movement Trajectory	Capture toe force and balance adjustment

Sensor nodes are connected to the waist-mounted data acquisition module via flexible wires. The acquisition module integrates a microcontroller (STM32L476), a Bluetooth 5.2 module, and a lithium battery (500 mAh capacity, 12-hour endurance) to enable data aggregation and wireless transmission [23].

C. DATA TRANSMISSION LAYER DESIGN

A dual-mode Bluetooth 5.2 and WiFi communication architecture is adopted:

1. For short-range scenarios (<10m), Bluetooth 5.2 communication is used with a transmission rate of 2 Mbps and latency <10ms, suitable for close-range applications like dance instruction.

2. For long-range scenarios (<100m), WiFi communication is employed with a transmission rate of 150 Mbps and latency <20ms, meeting the demands of large-scale applications like stage performances.

Data transmission adopts a packet-based strategy, with each packet size set at 128 bytes. Each packet contains information including the sensor node ID, timestamp, and sensor data. CRC checksum verification ensures data transmission reliability [24,25].

D. INTERACTIVE FEEDBACK LAYER DESIGN

1) Visual Guidance Module

A Qt-based visual interface displays real-time information:

1. Motion data curves: Temporal variation curves for parameters like joint angles, angular velocities, and force;

2. Movement standard comparison: Real-time movement characteristics are compared against a standard movement feature database, with deviation zones highlighted in different colors (red: deviation >10%, yellow:
5%-10%, green: <5%);

3. Quantitative evaluation report: Generates a movement standard score (1-100 points) and improvement suggestions.

2) Vibration Feedback Module

Each sensor node integrates a miniature vibration motor (frequency range: 200–500 Hz) to generate vibration feedback of varying intensity based on movement deviation severity:

1. Minor deviation (<5%): No vibration;

2. Moderate deviation (5%–10%): Low-intensity vibration (200 Hz);

3. Severe deviation (>10%): High-intensity vibration (500 Hz), providing real-time alerts for dancers to adjust movements [26,27].

IV. DANCE MOVEMENT FEATURE EXTRACTION MODEL AND INTERACTION MECHANISM

A. DEFINITION OF DANCE MOVEMENT FEATURES

Dance movement features are categorized into static and dynamic features, as detailed in Table 2.

TABLE 2. Classification and Description of Dance Movement Features

Feature Type	Specific Features	Description
Static Features	Joint Angle, Limb Posture, Force Distribution	Reflect the instantaneous state of the movement, capturing the limb position and force situation at a certain moment
Dynamic Features	Angular Velocity, Acceleration, Movement Duration, Force Change Rate	Reflect the temporal changes of the movement, embodying the evolution of dynamic parameters during the movement process

For mainstream dance genres including classical dance (circular steps, cloud hands), modern dance (ground movements, jumps), and street dance (Breaking, Popping), we extract typical features of various actions to construct a standard action feature library. This library contains feature templates for 50 basic actions and 20 combination actions [28-30].

Multi-dimensional features specifically include kinematic, mechanical, and temporal dimensions. A jointchain-based algorithm is designed to infer fine motion features of torso, fingers, and toes through synergistic data analysis of core and newly added nodes.

B. CONSTRUCTION OF THE BI-GRU-ATTENTION FEATURE EXTRACTION MODEL

1) Model Architecture

The model adopts a six-layer structure: Input Layer → Feature Encoding Layer → Bi-GRU Layer → Attention Layer → Fully Connected Layer → Output Layer:

1. Input Layer: Inputs the multi-source fused feature vector with dimensions 64×T (where T is the sequence length);

2. Feature Encoding Layer: Extracts local features via a 1D convolutional layer (3×3 kernels, 64 channels) using ReLU activation;

3. Bi-GRU Layer: Consists of two Bi-GRU layers, each with 128 hidden units and a dropout rate of 0.3, capturing bidirectional temporal features;

4. Attention Layer: Weighted attention is applied to Bi-GRU outputs to enhance key action segment features;

5. Fully Connected Layers: Two fully connected layers with output dimensions of 64 and 32, respectively, employing BatchNorm to mitigate overfitting;

6. Output Layer: Action classification results are generated via Softmax activation, or feature vectors are output for action comparison.

2) Model Training

1. Dataset: Utilizes a self-built dance action dataset (see Chapter 5 for details), partitioned into training, validation, and test sets at a ratio of 7:2:1;

2. Training Parameters: Batch Size = 32, Learning Rate = 0.001, Training Iterations = 100, AdamW optimizer, Cross-Entropy Loss function;

3. Regularization Strategy: Employed L2 regularization (weight decay = 0.0001) and dropout mechanism to enhance model generalization.

C. REAL-TIME INTERACTION MECHANISM DESIGN

1) Action Feature Comparison Algorithm

Implemented Dynamic Time Warping (DTW) for real-time comparison between action features and the standard feature library, addressing inconsistent action durations. The core formula is as follows:

$$\begin{aligned} DTW(i,j) = d(x_i, y_j) + \min\{&DTW(i-1,j), \\ &DTW(i,j-1), DTW(i-1,j-1)\} \end{aligned} \quad (12)$$

Among these, x_i represents the feature at time step i of the real-time action, y_j denotes the feature at time step j of the reference action, $d(x_i, y_j)$ is the Euclidean distance, and $DTW(i,j)$ is the cumulative distance.

2) Interaction Feedback Process

1. Data Acquisition: The sensor network collects dance motion data in real time and transmits it to the data processing layer;

2. Preprocessing and Feature Extraction: Data undergoes preprocessing via Kalman filtering and temporal alignment before input into the Bi-GRU-Attention model for feature extraction;

3. Motion Comparison: The DTW algorithm compares real-time features against the standard feature library to compute deviation values;

4. Feedback Generation: Visual guidance and vibration feedback are generated based on deviation values, with feedback latency controlled within 50ms.

V. EXPERIMENTAL VALIDATION AND PERFORMANCE ANALYSIS

A. EXPERIMENTAL ENVIRONMENT AND DATASET

1) Experimental Environment

Hardware: Flexible textile sensor network (9 composite sensor nodes), STM32 data acquisition module, PC (Intel Core i7-12700H CPU, 16GB RAM), vibration feedback module; Software: Python 3.9, PyTorch 2.0, Qt 5.15, MATLAB 2023 (for data processing).

2) Self-Built Dance Movement Dataset

1. Data Collection: Ten dance majors (5 male, 5 female, aged 18–22) participated in data collection, covering three dance genres (classical, modern, street dance), 50 basic movements, and 20 combination movements. Each movement was repeated 10 times, yielding 7,000 movement samples. This study was approved by the Ethics Committee of ChengDu Vocational University of the Arts, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

2. Data Annotation: Two dance instructors annotated the motion samples, labeling motion types and standard feature values. Annotation consistency Kappa coefficient = 0.89;

3. Dataset Division: Training set (4,900 samples), validation set (1,400 samples), test set (700 samples). Five professional street dancers (specializing in Breaking and Popping) underwent a 2-hour specialized ground movement test for practical validation.

B. COMPARISON MODELS AND EXPERIMENTAL SETUP

1) Comparison Models

Five mainstream motion feature extraction models were selected for comparison:

1. Traditional machine learning models: Support Vector Machine (SVM), Random Forest (RF);

2. Single deep learning models: CNN, LSTM, GRU;

3. Enhanced deep learning models: Bi-GRU, CNN-Attention, LSTM-Attention;

4. Traditional motion capture systems: Optical tracking system (OptiTrack), standalone IMU sensor system;

5. Recent relevant models: Transformer-based action extraction models.

2) Experimental Setup

1. Feature extraction performance experiments: Testing Motion Classification Accuracy and RMSE of each model on a self-built dataset;

2. Real-time performance experiments: Measuring system response latency during motion capture across different dance genres;

3. Wearability experiments: Inviting 20 professional dancers to wear the system during a 1-hour dance training session and rate comfort;

4. Robustness Experiment: Test system performance under varying environmental conditions (temperature 15–35°C, humidity 30%–70%);

5. Scenario Application Experiment: Validate system practicality in dance instruction and stage performance settings.

Sampling rate validation experiment: Compare motion feature capture accuracy at 100 Hz and 200 Hz; Power consumption test: Quantify each module's power consumption with professional equipment

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) Feature Extraction Performance Analysis

Motion Classification Accuracy and RMSE comparisons across models are shown in Table 3.

TABLE 3. Comparison of Motion Classification Accuracy, RMSE, and Advantages/Disadvantages of Different Models

Model	Motion Classification Accuracy (%)	RMSE	Core Advantages / Disadvantages
SVM	72.3	0.186	Traditional machine learning model, weak in capturing temporal features
RF	75.6	0.162	Ensemble learning model, general generalization ability
CNN	83.5	0.125	Good at local feature extraction, insufficient in capturing temporal correlations
LSTM	85.7	0.108	Can capture temporal features, obvious gradient vanishing problem
GRU	86.9	0.097	Optimizes gradient vanishing, better at capturing temporal features than LSTM
Bi-GRU	89.4	0.082	Captures temporal features bidirectionally, lacks focus on key actions
CNN-Attention	90.1	0.078	Strengthens local key features, insufficient in global temporal capture
LSTM-Attention	91.5	0.069	Combines temporal features and attention, weak in bidirectional capture
Transformer-based	93.2	0.054	Strong in global feature capture, poor real-time performance
Our Bi-GRU-Attention	95.7	0.038	Bidirectional temporal + key action weighting, balanced accuracy and efficiency
ViT	92.8	0.059	Strong in global feature capture, poor real-time performance
GCN	93.5	0.052	Effective in modeling spatial joint relationships, weak in temporal feature capture
ST-TR	94.3	0.045	Integrates spatio-temporal features, high computational complexity

As shown in Table 3, our model achieves an Motion Classification Accuracy of 95.7%, outperforming traditional machine learning models by 20.1%-23.4%, surpassing single deep learning models by 8.8%-12.2%, and exceeding other improved models by 2.5%-4.2%. With an RMSE as low as 0.038, it significantly outperforms the comparison models. This superiority stems from the Bi-GRU-Attention model's integration of bidirectional temporal feature capture with key action attention weighting, enabling precise extraction of dynamic variations and subtle distinctions in dance movements. Sampling rate validation: Peak acceleration capture error for Popping at 200 Hz is 2.1% (vs. 8.3% at 100 Hz); Breaking spin angular velocity accuracy reaches 96.8%. Sensor network optimization improves feature extraction completeness by 42%.

2) Real-Time Performance Analysis

Response latency comparisons across systems are presented in Table 4.

TABLE 4. Comparison of Response Latency of Different Motion Capture Systems

System Type	Data Transmission Delay	Feature Extraction Delay	Feedback Generation Delay	Total Delay	Application Scenarios
Optical Motion Capture System	35	42	28	105	High-precision laboratory scenarios
Single IMU Sensing System	18	35	22	75	Simple motion capture scenarios
Transformer-based System	12	28	15	–	Scenarios with low real-time requirements
Our System	10	25	12	47	Real-time interaction scenarios such as dance teaching and stage performance

The total response latency of this system is only 47ms, below the 50ms threshold required for real-time interaction. Compared to optical tracking systems, latency is reduced by 55.2%, and compared to single-IMU systems, it is reduced by 37.3%. This improvement stems from the low-latency transmission enabled by dual-mode communication and the efficient feature extraction capabilities of the Bi-GRU-Attention model.

3) Wear Comfort and Robustness Analysis

Wear comfort evaluation results indicate that the proposed system achieved a comfort score of 8.9 (out of 10), significantly higher than the single IMU system (7.2) and the optical tracking system (no wearability score due to venue constraints). The soft and breathable design of the flexible textile sensor nodes effectively minimized restrictions on dance movements, earning high recognition from dancers.

Robustness experiments demonstrate that under environmental conditions of 15–35°C temperature and 30–70% humidity, the motion classification accuracy of this system fluctuates within ±0.8%, with RMSE variation of ±0.003. This exhibits strong environmental adaptability, meeting application requirements across diverse scenarios.

4) Ablation Study Analysis

To validate the effectiveness of each model component, ablation experiments were conducted. Results are presented in Table 5.

TABLE 5. Ablation Experiment Results of the Bi-GRU-Attention Model

Model Configuration	Motion Classification Accuracy (%)	Performance Drop Rate (%)	Module Function Description
Our Complete Model (Bi-GRU-Attention + Feature Encoding Layer)	95.7	–	The three modules collaborate to achieve optimal performance
Remove Attention Mechanism (Bi-GRU + Feature Encoding Layer)	89.4	6.3	The attention mechanism is the core for strengthening key action features
Remove Bidirectional Structure (GRU-Attention + Feature Encoding Layer)	91.2	4.5	The bidirectional structure improves the comprehensiveness of temporal features
Remove Feature Encoding Layer (Bi-GRU-Attention)	93.5	2.2	The feature encoding layer enhances local feature extraction capability

Dissolution experiments demonstrate that the attention mechanism most significantly enhances model performance, with its key action-weighting capability serving as the core for accurately extracting dance motion features. The bidirectional GRU structure strengthens comprehensive capture of temporal features, while the feature encoding layer improves local feature extraction. The synergistic interaction of these three components achieves optimized model performance.

VI. CONCLUSIONS AND OUTLOOK

Addressing core requirements for dance motion capture and real-time interaction, this study designed a dance motion feature extraction and real-time interaction system based on flexible textile sensor networks. Key achievements include:

1. Constructed a flexible pressure-inertia composite sensor network, optimized sensor node deployment and encapsulation design, enabling unrestricted, high-precision collection of multidimensional dance motion data with wear comfort rated at 8.9 points;
2. Proposed a multi-source data fusion preprocessing strategy. Noise interference was suppressed through Kalman filtering and temporal alignment algorithms, enhancing data reliability;
3. Designed a Bi-GRU-Attention motion feature extraction model. Combining bidirectional temporal feature capture with key motion attention weighting achieved 95.7% motion classification accuracy and an RMSE as low as 0.038;
4. Established an integrated real-time "acquisition-extraction-feedback" interactive system. Utilizing dual-mode communication and DTW alignment algorithms, the system achieves response delays under 50ms, enabling collaborative visualization guidance and vibration feedback.

Future research can deepen in three areas:

1. Sensor network optimization: Develop flexible multi-parameter sensing nodes (humidity, temperature) and integrate physiological data (heart rate, respiration) to achieve collaborative perception of dance movements and emotional states;
2. Model Enhancement: Incorporate transfer learning and federated learning techniques to improve model generalization for niche dance styles and personalized movements while safeguarding data privacy;
3. Application Expansion: Develop mobile interactive apps and cloud-based data platforms for long-term storage, analysis, and sharing of motion data, fostering an intelligent ecosystem for dance education.

AUTHOR CONTRIBUTIONS

Conceptualization –Wang Qinyi and Hu Yijie; methodology – Wang Qinyi and Hu Yijie; investigation – Wang Qinyi and Hu Yijie; writing-original draft preparation – Wang Qinyi and Hu Yijie. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of ChengDu Vocational University of the Arts, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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Not applicable.

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