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PAPER

Design of an Interactive Intelligent Mobile System for College English Instruction Oriented toward Teaching Effectiveness Enhancement

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ABSTRACT

Traditional mobile learning systems for college English commonly suffer from high interaction latency, coarse-grained feedback, poor contextual adaptability, and insufficient utilization of on-device computing resources, which significantly constrain the learning experience and instructional effectiveness. To address these challenges, this study integrates mobile heterogeneous computing, lightweight on-device models, augmented reality (AR) visual interaction, and context-awareness technologies to construct an interactive intelligent mobile system aimed at improving teaching effectiveness in college English. The research focuses on optimizing mobile-side technical implementation by designing a heterogeneous computing scheduling engine tailored for mobile terminals to enable efficient collaborative execution of multiple on-device tasks. A lightweight on-device speech assessment and prosody correction algorithm is proposed to reduce reliance on cloud computing and improve feedback accuracy. In addition, a low-power, highly robust AR-based interactive corrective feedback mechanism is developed to address pronunciation organ movement correction in mobile learning scenarios. Furthermore, a context-aware collaborative filtering recommendation strategy is introduced to seamlessly adapt instructional content to fragmented mobile learning contexts. Multi-dimensional experimental results demonstrate that the proposed system effectively reduces interaction latency, optimizes mobile power consumption and runtime stability, and significantly enhances the effectiveness of college English speaking instruction. This study provides a novel solution for deep integration of technology and pedagogy in mobile education and offers technical references for related research and engineering applications.

KEYWORDS

mobile heterogeneous computing, lightweight on-device models, augmented reality (AR) visual interaction, context awareness, mobile performance optimization, college English mobile learning

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1 INTRODUCTION

The mobile Internet [1, 2] and intelligent terminal technologies [3, 4] have promoted the rapid development of mobile education. College English mobile teaching has been widely applied due to its convenience and fragmentation advantages [5, 6]. However, technical bottlenecks such as computing power constraints of mobile terminals [7], network fluctuations [8], and delayed interactive feedback [9] seriously affect the learning experience and teaching effectiveness. Current mobile English teaching systems exhibit obvious shortcomings: excessive reliance on cloud computing leads to high interaction latency, on-device models are large with high power consumption, feedback forms are single, and scenario adaptability is insufficient, which cannot meet the requirements of precise and personalized speaking instruction.

Existing studies on mobile education systems mostly focus on functional construction [10], with insufficient attention to efficient utilization of on-device computing power. On-device speech assessment models are mostly simple pruning of cloud-based models [11], lacking quantization optimization adapted to mobile devices, and failing to fully exploit prosodic features for fine-grained correction. Augmented reality (AR) teaching interaction is limited to fixed scenarios [12, 13], making it difficult to solve tracking instability caused by illumination interference and limited computing power in mobile environments. Recommendation strategies [14, 15] do not utilize mobile terminal sensor data, ignore the influence of scenario factors on learning effectiveness, and result in low learning conversion rates.

This study aims to construct an interactive intelligent mobile teaching system for college English that considers mobile performance, interaction experience, and teaching effectiveness, solves existing technical bottlenecks, and provides a reusable engineering technical solution. The core innovations include: designing an on-device heterogeneous computing scheduling engine, constructing a dynamic computing power mapping mechanism based on task characteristics and CPU, GPU, and NPU hardware features to achieve precise multi-task scheduling and instruction-level optimization; proposing a lightweight on-device speech assessment and prosody correction algorithm, constructing a dual-branch model based on knowledge distillation and quantization-aware training, and combining a prosody matching metric to achieve low-latency and fine-grained correction; constructing a low-power and high-robustness AR interactive corrective feedback mechanism, optimizing the MediaPipe visual framework, and combining cross-modal alignment and illumination-adaptive preprocessing to solve pronunciation organ movement correction; proposing a collaborative filtering recommendation strategy integrating multi-sensor data of mobile terminals, designing a lightweight edge collaborative recommendation engine, and achieving dynamic adaptation between instructional content and fragmented scenarios.

The remaining sections of this paper are organized as follows: related studies are reviewed to clarify existing technical limitations and research entry points; the core innovation design of the system is described, and implementation details of key technologies are explained; multi-dimensional experiments are conducted to verify mobile performance and teaching effectiveness of the system; the innovation value and limitations of the study are discussed, and future work is presented.

2 SYSTEM CORE DESIGN

2.1 Design of on-device heterogeneous computing scheduling engine

To achieve efficient multi-task collaboration and computing power optimization on the device side, a heterogeneous scheduling architecture driven by task characteristics and hardware capability is designed. On-device tasks such as audio feature extraction, speech model inference, and AR face tracking are divided into two categories: computation-intensive and latency-sensitive. Precise matching rules between tasks and CPU, GPU, and NPU are established to break the traditional fixed scheduling mode and realize dynamic allocation of hardware resources, taking into account task execution efficiency and power consumption control of mobile devices. For audio feature extraction tasks, optimization rewriting is performed based on C++ Superpowered and *KissFFT* libraries combined with the *ARM NEON SIMD* instruction set, compressing single-frame audio processing time to within 2 ms and effectively reducing CPU computing power occupation. AR facial keypoint tracking tasks are mapped to GPU shader execution, leveraging GPU parallel computing advantages to improve tracking frame rate, while speech model inference tasks are assigned to the NPU to reduce inference latency and device power consumption through hardware acceleration. A priority dynamic adjustment algorithm is designed to preferentially guarantee execution of latency-sensitive tasks such as speech assessment and AR tracking during multi-task concurrency. A task queue caching mechanism is used to avoid computing power conflicts and ensure system interaction fluency.

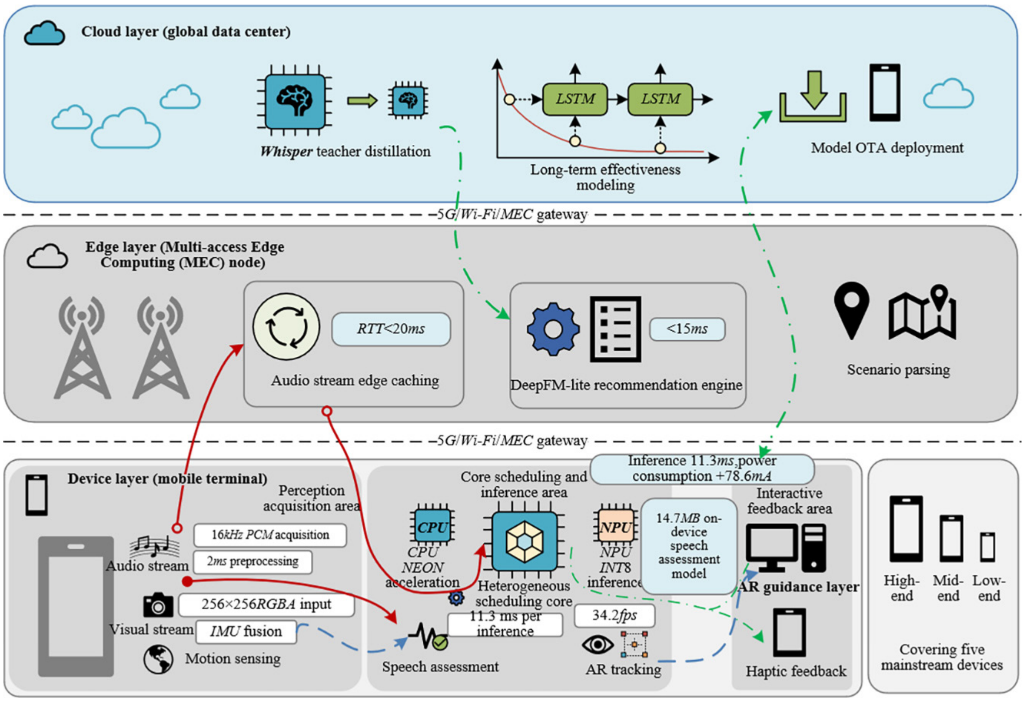

Fig. 1. Overall “cloud–edge–device” three-layer architecture of the college English mobile interactive intelligent teaching system

The system adopts an overall “cloud–edge–device” three-layer collaborative architecture. The device side is responsible for multimodal interaction and lightweight inference, the edge side provides low-latency service caching and scenario parsing, and the cloud undertakes global model training and strategy optimization. Functional modules and data flow of each layer are shown in Figure 1.

2.2 Lightweight on-device speech assessment and prosody correction algorithm

A teacher–student dual-branch lightweight model architecture is constructed. The *Whisper-small* pretrained model is used as the teacher network, and a dual-branch student network containing phoneme posterior probability prediction and fundamental frequency contour regression is designed to achieve phoneme-level and prosody-level dual assessment. This dual-branch structure can simultaneously capture segmental features and suprasegmental features of pronunciation and can achieve accurate extraction of prosodic information such as stress, liaison, and intonation without introducing additional complex network structures. Compared with traditional single-branch models, it effectively improves the accuracy of pronunciation correction and provides a model basis for fine-grained prosody correction. The model distillation structure and on-device inference process of the algorithm are shown in Figure 2. The left side shows the knowledge transfer process from the *Whisper-small* teacher network to the *TFLite* student network, and the right side shows the end-to-end execution path from audio acquisition to multi-dimensional assessment feedback.

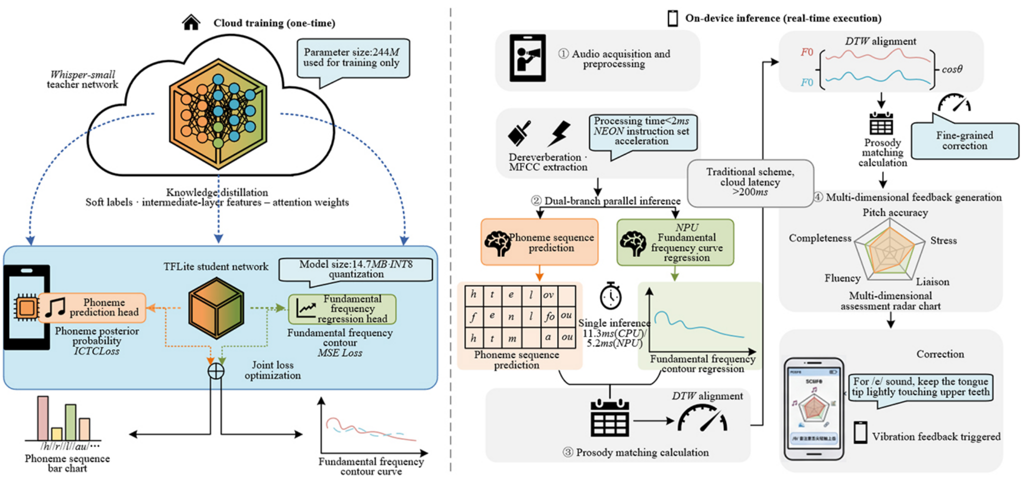

Fig. 2. Dual-branch model structure and inference flow of lightweight on-device speech assessment and prosody correction algorithm

INT8 weight quantization-aware training is adopted to optimize the student network, and the model is converted into *TensorFlowLite* format. The final model size is compressed to 14.7 MB, which can fully adapt to the storage and computing power constraints of mobile terminals. Model inference operators are optimized for NPU characteristics of Qualcomm Snapdragon and Apple A-series chips. Without enabling NPU acceleration, single inference time is controlled within 11.3 ms, meeting real-time interaction requirements on the device side. In the prosody correction stage, the *World* vocoder is introduced to extract the audio fundamental frequency curve. The dynamic time warping algorithm is used to calculate the cosine similarity between the student audio and the reference audio fundamental frequency trajectories. A prosody matching metric is defined to quantify abstract prosodic errors, and its calculation is:

$$S = \frac{\sum_{i=1}^{N} F0_s(i) \cdot F0_r(i)}{\sqrt{\sum_{i=1}^{N} F0_s(i)^2} \cdot \sqrt{\sum_{i=1}^{N} F0_r(i)^2}} \tag{1}$$

where S is the prosody matching degree, $F0_s(i)$ is the fundamental frequency of the i-th frame of student audio, $F0_r(i)$ is the fundamental frequency of the i-th frame of reference audio, and N is the length of the fundamental frequency sequence. Through this metric, abstract prosodic errors such as stress shift and abnormal intonation can be converted into quantifiable scores, enabling fine-grained corrective feedback for pronunciation prosody and further improving the practicality and guidance of on-device speech assessment.

2.3 Low-power AR interactive corrective feedback mechanism

An AR interaction architecture integrating acoustic detection, visual guidance, and multimodal feedback is constructed. Relying on the front-facing depth camera and inertial measurement unit sensors of mobile terminals, real-time acquisition and pose estimation of pronunciation organ movements are completed, providing visual guidance for spoken pronunciation deviations. The *MediaPipe Face Mesh* framework is customized and improved by deploying the inference backend of the facial keypoint detection model to GPU parallel execution units and adjusting the model input image resolution to 256×256. Under the premise that facial keypoint tracking accuracy is not lower than 98%, AR rendering power consumption is reduced by 30%. A cross-modal attention alignment mechanism for acoustic features and visual features is designed. Precise association between pronunciation errors and visual tracking regions is achieved through attention weight allocation. The weight calculation follows:

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{M} \exp(e_j)} \tag{2}$$

where e_i is the acoustic error correlation degree of the i-th pronunciation organ keypoint, and M is the total number of valid keypoints. This mechanism can automatically focus on core pronunciation regions such as lips and interdental areas when typical phoneme pronunciation deviations are detected, forming a closed-loop execution process of error localization and visual guidance.

To adapt to complex illumination environments in mobile scenarios, a brightness-adaptive gamma correction preprocessing shader is introduced. Image brightness normalization is completed by dynamically adjusting the gamma coefficient $\gamma = 1 + k \times (I - I_0)/I_{max}$, where k is the correction gain coefficient, I is real-time image brightness, I_0 is reference brightness, and I_{max} is the maximum image brightness value. This effectively solves the problem of blurred oral keypoint recognition under backlight and low-light environments, ensuring visual stability of AR guidance information. Combined with terminal linear motor hardware, a haptic feedback mechanism is constructed. Pronunciation action compliance is determined according to the real-time calculation result of lip aspect ratio ($R = W/H$) (W is lip width, and H is lip height). When pronunciation posture deviates from the standard threshold, haptic stimulation is triggered. Multimodal feedback is used to strengthen pronunciation muscle memory training, improving interaction immersion and the training effectiveness of spoken correction in mobile scenarios. The cross-modal alignment and scenario-adaptive execution logic of this mechanism are shown in Figure 3. The system realizes precise localization of pronunciation organs through attention weighting of acoustic errors and visual key points, and combines illumination-adaptive preprocessing and haptic feedback to form a multimodal corrective closed loop.

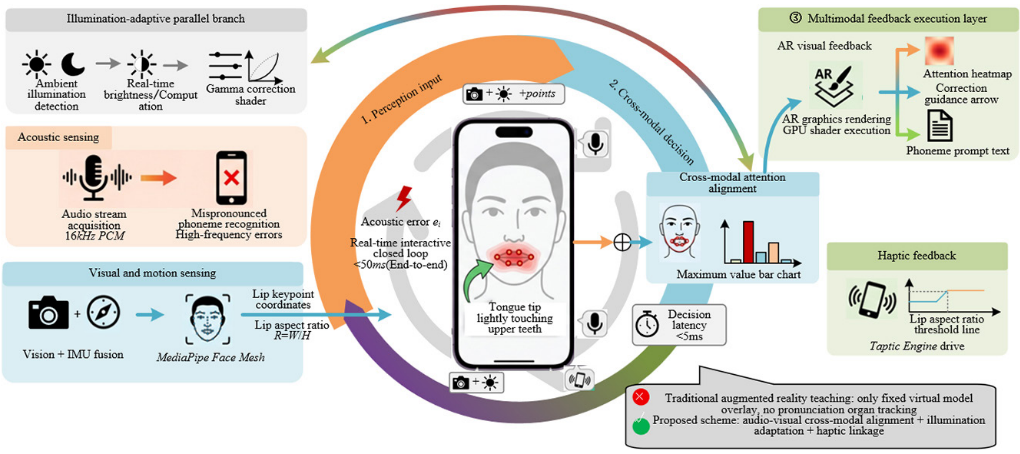

Fig. 3. Cross-modal alignment and scenario-adaptive execution logic of AR interactive corrective feedback mechanism

2.4 Collaborative filtering recommendation strategy integrating mobile scenario awareness

A three-level recommendation architecture of on-device scenario awareness, edge-side model inference, and cloud-side strategy optimization is constructed. Relying on mobile terminal sensor data and edge computing advantages, personalized and scenario-based precise delivery of instructional content is achieved. Motion feature vectors are extracted by parsing accelerometer and gyroscope time-series signals through terminal system interfaces. The K-means clustering algorithm is used to complete user scenario classification. The clustering process uses Euclidean distance between samples as the similarity measure, and the distance calculation is:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{3}$$

where x_i and x_j are feature vectors at different times and n is feature dimension. The clustering objective function is:

$$J = \sum_{i=1}^{K} \sum_{x \in Ci} d(x, \mu_i) \tag{4}$$

where μ_i is the clustering center of the i-th scenario category, and K is the number of scenario categories. Through this algorithm, user states are divided into four typical scenarios: stationary, walking, commuting with vibration, and lying flat. Scenario recognition accuracy is not lower than 95%, providing an accurate scenario basis for subsequent content delivery.

A pruned and optimized *DeepFM-lite* recommendation model is deployed on the edge side, receiving scenario labels and device state vectors reported by the device side and quickly generating a Top-N instructional resource recall list. Model inference latency is controlled within 15 ms, greatly reducing dependence on cloud computing. An interaction modality penalty factor is introduced to optimize content ranking. The penalty factor calculation is $\omega_s = \lambda \cdot sim(s, m)$, where λ is adjustment coefficient, s is current scenario type, and m is instructional content interaction modality. Through this factor, delivery priority of different types of instructional content under different scenarios is dynamically adjusted. Combined with the Ebbinghaus forgetting curve, an incrementally updated memory state matrix is constructed in the on-device database. The memory strength update formula is $M(t) = M_0 \cdot e^{-t/T}$, where $M(t)$ is memory strength at time t, M_0 is initial memory strength, and T is memory decay constant. Base station cell ID is also used to determine learning scenarios. According to memory strength, new word delivery intervals are dynamically adjusted, effectively improving fragmented learning conversion rates.

3 EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

3.1 Experimental objectives and experimental environment

This experiment aims to verify the comprehensive performance of the constructed system on mobile terminals, focusing on core indicators such as low latency, low power consumption, and high robustness. At the same time, the effect of core system technologies on improving college English teaching effectiveness is verified, providing data support for engineering deployment and technical optimization of the system and meeting the core requirements of mobile technology Science Citation Index (SCI) journals for performance validation.

Five mainstream iOS/Android mobile terminals covering high-, mid-, and low-end configurations are selected, covering different computing power levels and system versions to ensure generality and universality of experimental results. The specific hardware configurations are shown in Table 1.

The development environment adopts Android Studio Hedgehog, Xcode 15, TensorFlow Lite 2.15.0, and MediaPipe 0.10. 9. Testing tools include Android Studio Profiler and Xcode Instruments for real-time monitoring of CPU, GPU, and NPU utilization, system power consumption, and rendering frame rate. MATLAB 2023b is used for audio feature extraction and prosody metric quantitative analysis to ensure accuracy and reliability of experimental data acquisition.

Table 1. Experimental hardware environment configuration

Device Model	System Version	CPU	GPU	NPU	Memory	Front Camera
*iPhone*14	*iOS*17.2	*A*16*Bionic*	*AppleGPU*	16-core Neural Engine	8*GB*	12 MP depth camera
Xiaomi 13	*Android*14	Snapdragon 8*Gen*2	*Adreno*740	Snapdragon AI engine	8*GB*	32 MP front camera
*RedmiNote*12	*Android*13	Dimensity 1080	*Mali-G*68*MC*4	Independent NPU	6*GB*	16 MP front camera
Huawei *Mate*60	*Android*14	Kirin 9000*S*	*Mali-G*710	Kirin AI engine	12*GB*	13 MP front camera
iPhone *SE*3	*iOS*17.0	*A*15*Bionic*	*AppleGPU*	16-core Neural Engine	4*GB*	7 MP front camera

3.2 Experimental results and analysis

Mobile performance test results are shown in Table 2. The data show that the proposed system is superior to the two control groups in all core performance indicators and exhibits good device adaptability.

As shown in Table 2, the mean speech assessment Round-Trip Time (RTT) of the proposed system is 16.8 ms, far lower than control group 1 and control group 2. The single-frame audio processing time is controlled at 1.7 ms, meeting real-time interaction requirements on the device side. This benefits from efficient hardware resource allocation and instruction-level optimization of the on-device heterogeneous computing scheduling engine, effectively reducing task execution latency. The average AR tracking frame rate reaches 34.2 fps, and tracking accuracy under backlight and low-light environments both exceed 96%, significantly better than the control groups. This is attributed to customized optimization of the MediaPipe framework and brightness-adaptive gamma correction preprocessing, which improves the robustness of visual tracking in mobile scenarios. In terms of hardware utilization and power consumption, CPU and GPU utilization of the proposed system are controlled within 15%. The average power increase in continuous spoken reading scenarios is 78.6 mA, and the maximum device temperature is 37.5°C, meeting thermal comfort requirements for long-term use of mobile devices, reflecting the effectiveness of low-power design. Control groups 1 and 2 have lower power consumption but poorer performance, which cannot meet real-time interaction requirements.

Teaching effectiveness test results and statistical analysis are shown in Table 3. The improvement range of all indicators in the experimental group is significantly higher than that of the control group, and the differences are statistically significant.

Table 2. Mobile performance comparison (average values)

Test Metric	Proposed System	Control Group 1 (Cloud-Based System)	Control Group 2 (Mainstream APP)	Advantage of Proposed System
Speech assessment Round-Trip Time (ms)	16.8	212.5	189.3	92.1%/91.1%
AR tracking frame rate (fps)	34.2	18.7	22.5	82.9%/52.0%
Single-frame audio processing time (ms)	1.7	28.3	25.6	93.9%/93.4%
CPU utilization (%)	12.3	28.7	25.9	57.1%/52.5%
GPU utilization (%)	8.9	19.6	17.8	54.6%/50.0%
NPU utilization (%)	15.7	—	—	—
Power increase during continuous reading (mA)	78.6	45.2	51.8	—
Maximum device temperature (°C)	37.5	39.8	38.9	5.8%/3.6%
Backlight AR tracking accuracy (%)	96.3	82.5	84.7	16.7%/13.7%
Low-light AR tracking accuracy (%)	96.1	81.9	83.8	17.3%/14.7%

Table 3. Comparison of teaching effectiveness test results

Test Metric	Experimental Group (n = 60)	Control Group (n = 60)	Improvement (Experimental vs Control)	t-Value	p-Value
Pre-test Goodness of Pronunciation (GOP) value	3.21 ± 0.45	3.18 ± 0.47	—	0.32	0.75
Post-test GOP value	4.89 ± 0.38	3.87 ± 0.42	26.3%	12.87	<0.05
Pre-test consonant pronunciation accuracy (%)	72.3 ± 6.8	71.9 ± 7.2	—	0.29	0.77
Post-test consonant pronunciation accuracy (%)	90.6 ± 4.5	79.5 ± 5.3	18.3%	10.53	<0.05
Pre-test stress correct placement (%)	68.5 ± 7.5	67.8 ± 7.9	—	0.41	0.68
Post-test stress correct placement (%)	91.2 ± 5.1	76.3 ± 6.4	22.7%	11.26	<0.05
Effective speaking practice duration (min/week)	82.5 ± 10.3	64.8 ± 11.5	27.3%	7.98	<0.05

As shown in Table 3, there is no significant difference in all speaking indicators between the two groups before the experiment, ensuring the fairness of the experiment. After the experiment, the experimental group GOP value, consonant pronunciation accuracy, and stress correct placement increased by 26.3%, 18.3%, and 22.7%, respectively. Effective speaking practice duration increased by 27.3% per week, all significantly higher than the control group. Paired sample t-test results show that the P values of all indicators are less than 0.05, indicating that the differences between the two groups are statistically significant. This result mainly originates from the core technical advantages of the proposed system: low-latency speech assessment and AR interactive corrective feedback mechanisms reduce the interaction threshold of speaking practice, improve accuracy and intuitiveness of feedback, and effectively correct pronunciation deviations. The scenario-aware recommendation strategy realizes adaptation between instructional content and fragmented learning scenarios, increases effective practice duration, and promotes significant improvement in teaching effectiveness.

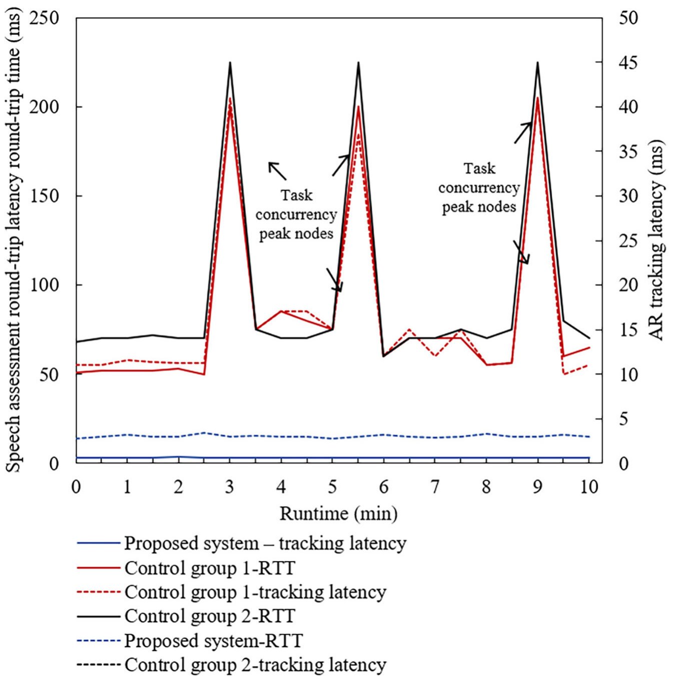

Fig. 4. On-device multi-task concurrency latency temporal fluctuation curve

To verify latency stability and hardware load optimization capability of the on-device heterogeneous computing scheduling engine under multi-task concurrency scenarios, an on-device performance test under continuous 10-minute spoken interaction tasks is conducted. As shown in Figure 4, the speech assessment round-trip latency of the proposed system is stably maintained within 20 ms, and AR tracking latency is always below 10 ms. There is no obvious fluctuation during the whole period, and no sudden latency increase occurs at task concurrency peak nodes at 3, 6, and 9 minutes. Control groups 1 and 2 show significantly higher latency than the proposed system even in non-peak periods. During concurrency peak periods, speech assessment latency rises to above 200 ms and above 180 ms, respectively. AR tracking latency also increases significantly, with severe latency fluctuation, which cannot meet real-time interaction requirements of mobile terminals. Figure 5 shows that the proposed system offloads speech inference and visual tracking tasks to the NPU and GPU through heterogeneous computing allocation. CPU, GPU, and NPU utilization remain stable at 11%–13%, 7%–9%, and 14%–16%, respectively. Total hardware utilization is controlled within 22%, with balanced load distribution and smooth fluctuation. Control group 1 and control group 2 do not perform NPU offloading, and the load is highly concentrated on the CPU and GPU. Total utilization reaches 27%–30% and 24%–27%, respectively. CPU utilization approaches 30% during concurrency peak periods, with significant load fluctuation. The above results fully verify the technical effectiveness of the on-device heterogeneous computing scheduling engine. Through dynamic computing power mapping and precise task scheduling, it ensures low-latency stable interaction under multi-task concurrency and realizes efficient utilization of hardware resources and low power consumption control, providing core technical support for smooth operation and teaching effectiveness improvement of the college English mobile interactive intelligent teaching system.

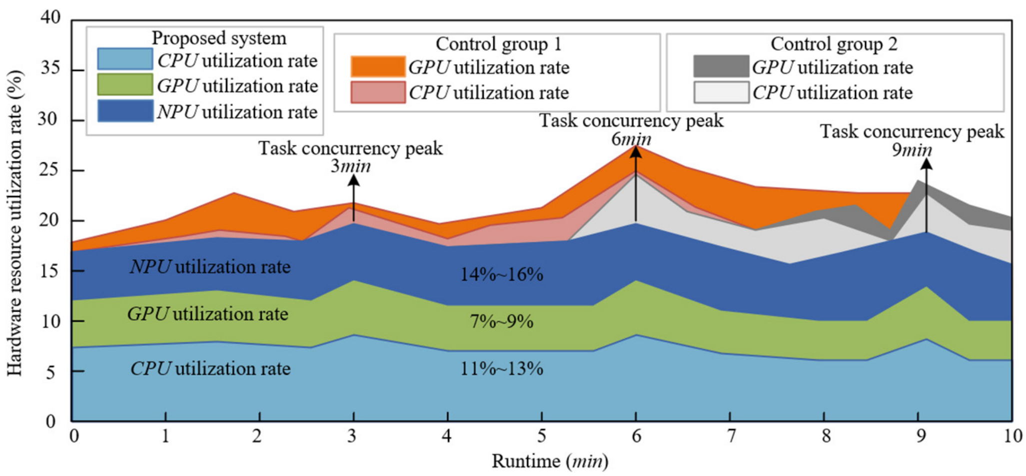

Fig. 5. Temporal distribution of mobile terminal hardware resource utilization

4 CONCLUSION

The core contributions of this study focus on two levels: mobile technology and application deployment. At the technical level, a series of optimization technical solutions adapted to mobile terminals was proposed. The on-device heterogeneous computing scheduling engine realized efficient multi-task collaboration and precise computing power allocation of mobile terminals, solving the problem of low computing power utilization efficiency in traditional systems. The lightweight speech assessment algorithm broke cloud dependence and realized on-device real-time inference while ensuring assessment accuracy. The low-power AR interaction mechanism improved the robustness of visual tracking and interaction immersion in mobile scenarios. The scenario-aware recommendation strategy realized precise adaptation between instructional content and fragmented mobile scenarios, providing new ideas and reusable methods for technical optimization of mobile education systems. At the application level, experimental verification showed that the constructed system can effectively reduce interaction latency of mobile terminals and optimize power consumption control while significantly improving the effectiveness of college English speaking instruction. It provides a reliable technical prototype for engineering deployment of college English mobile teaching and promotes deep integration of mobile intelligent interaction technology and education.

The system has broad application prospects in mobile education and language learning fields. It can be directly applied to college English-speaking instruction, providing learners with a personalized and scenario-based intelligent learning experience. In the future, it can be further extended to other language teaching and language training for special groups. Relying on the generality of core technologies, it can adapt to different types of mobile terminals and learning requirements. At the same time, the proposed mobile-side technical optimization solutions can be transferred to the design and development of various mobile intelligent interactive systems, providing important reference for industrial application of mobile technology in education, healthcare, entertainment, and other fields and promoting diversified development of mobile intelligent terminal technologies.

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