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Fine-Grained Action Analysis for Automated Skill Assessment and Feedback in Instructional Videos

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Abstract: Fine-grained action analysis in instructional videos presents significant challenges due to subtle motion variations and complex temporal dependencies. This paper introduces a comprehensive framework for automated skill assessment and feedback generation based on granularity-aware feature extraction and multi-modal fusion techniques. The proposed approach incorporates a temporal self-similarity module that captures periodic patterns critical for skill quality assessment, a part-level feature extraction network that analyzes body part movements, and a cross-attention transformer architecture that integrates skeleton and RGB modalities. Experiments conducted on our newly collected Skill Video dataset, comprising 8450 instructional videos across sports, crafts, medical procedures, and musical performances, demonstrate substantial improvements over state-of-the-art methods. The framework achieves 89.5% accuracy in skill level classification, a 20.1% reduction in dimensional assessment error, and a 5.8% improvement in temporal action quality estimation compared to existing approaches. User studies with 45 participants reveal that feedback generated by our system produces learning outcomes comparable to human expert guidance, with only a 3.6% gap in skill improvement and 2.6% difference in retention, as supported by rigorous experimental design and statistical analysis. The proposed technology enables personalized learning experiences through continuous assessment and feedback, with applications spanning formal education, professional training, and self-directed learning environments.

Keywords: fine-grained action recognition; skill assessment; multi-modal fusion; automated feedback generation

1. Introduction

1.1. Research Background and Motivation

Instructional videos have emerged as a prevalent medium for skill acquisition across various domains including education, healthcare, sports, and occupational training. The ubiquity of video-sharing platforms has led to an explosion in instructional content, creating unprecedented opportunities for self-directed learning. Despite this abundance, learners often struggle to receive personalized assessment and feedback on their skill execution. Research by Ou et al. demonstrates that fine-grained action analysis offers significant potential for automated skill assessment by detecting subtle motion variations that distinguish expert from novice performance [1]. Traditional action recognition frameworks typically focus on coarse-grained classification tasks, which inadequately address the nuanced requirements of skill assessment in instructional contexts.

The granularity level at which actions are analyzed directly impacts the quality of subsequent assessment and feedback. As noted by Luo and Xiao, current systems often fail to capture the temporal self-similarity and periodicity information essential for evaluating skill quality [2]. Additionally, Zhang et al. identified that conventional approaches overlook the significance of granularity-aware contrastive learning, which is vital for distinguishing between visually similar actions that represent different skill levels [3]. These limitations underscore the need for specialized frameworks designed specifically for fine-grained analysis of instructional content.

1.2. Challenges in Fine-Grained Action Analysis for Skill Assessment

Fine-grained action analysis for skill assessment presents several technical challenges. The primary difficulty lies in identifying and quantifying subtle differences between similar action executions that signify varying levels of expertise. Lin et al. highlighted the complications in detecting lightweight fine-grained actions, noting that temporal and spatial variations may be minimal yet critically important for accurate skill evaluation [4]. The issue is compounded by the necessity to differentiate between stylistic variations and substantive differences in execution quality.

Another significant challenge involves the temporal segmentation of continuous instructional demonstrations into meaningful action units that correspond to discrete skill components. Traditional approaches that rely on predefined temporal boundaries often fail to accommodate the natural variations in execution speed and style. The integration of multimodal data sources introduces additional complexity, as skeletal data, RGB visual information, and contextual cues must be effectively combined to create a comprehensive understanding of skill execution. Ghimire demonstrated that revisiting skeleton-based action recognition approaches could substantially improve performance, suggesting untapped potential in multimodal analysis frameworks [5].

1.3. Research Objectives and Contributions

This research aims to develop a comprehensive framework for fine-grained action analysis in instructional videos that enables automated skill assessment and personalized feedback generation. The proposed approach addresses the limitations of existing systems by incorporating granularity-aware feature extraction mechanisms that capture subtle variations in action execution indicative of skill proficiency.

The primary contributions of this work include:

1) A novel granularity-aware feature extraction framework that combines skeletal and RGB information for comprehensive action understanding.
2) A self-similarity attention module that captures periodic patterns critical for skill quality assessment as inspired by Xu's work [6].
3) A multimodal fusion strategy that integrates complementary information from different modalities following the transformer-based approach recommended by Xu et al. [7].
4) An automated feedback generation system that translates fine-grained action analysis into actionable guidance for skill improvement.

The proposed system advances the state-of-the-art in instructional content analysis by enabling precise evaluation of skill execution quality and generating detailed, actionable feedback for learners across various domains [8].

2. Related Work

2.1. Fine-Grained Action Recognition Approaches

Fine-grained action recognition has evolved significantly to address the challenges of distinguishing subtle variations in visually similar actions. Recent approaches have shifted from holistic action representations toward more detailed analyses of motion components. Shu et al. proposed a novel Fine-grained Teacher-student CLIP (FT-CLIP) that

integrates body part analysis with holistic action recognition through knowledge distillation, enabling the model to capture subtle action distinctions while maintaining efficient inference [9]. Their approach demonstrated that analyzing individual body parts generates part-specific features that, when aggregated, provide a more nuanced understanding of complex actions.

In the domain of sports analysis, Liu et al. introduced a lightweight fine-grained action recognition network for basketball foul detection that emphasized the temporal relationships between frames [10]. Their approach divided video sequences into 8-frame units processed by 3DCNN blocks to extract subtle features indicative of fouls. The visualization of action score distributions revealed that normal actions exhibited more uniform patterns while foul actions displayed distinctive peaks, confirming the instantaneous nature of certain fine-grained actions.

Zhang et al. addressed the limitations of standard contrastive learning by introducing Granularity-Aware Contrastive Learning (GACon) [3]. This framework redefined sample-label relations based on action granularity, enabling models to pull samples closer to their coarse label cluster while benefiting from fine-grained supervision. Their Coarse-Cross-Fine Experts architecture facilitated bidirectional information exchange between granularity-distinct experts, demonstrating superior performance on fine-grained action recognition benchmarks [11].

2.2. Skill Assessment in Instructional Videos

Skill assessment in instructional videos requires specialized approaches beyond standard action recognition techniques. The evaluation of skill proficiency involves analyzing execution quality rather than merely classifying action types. Zhou introduced a Self-similarity Attention Module (SAM) that represents action periodicity using Temporal Self-similarity Matrices (TSM) and channel-wise excitation [12]. This approach proved particularly effective for distinguishing actions involving different repetition counts, such as "switch leap with 1 turn" versus "switch leap with 2 turns", highlighting the importance of periodic temporal features in skill assessment [6].

The evaluation of skill levels often depends on precise motion quality assessment. Xu et al. demonstrated that Sequential Skeleton RGB Transformer (SSRT) could effectively recognize fine-grained human-object interactions by combining skeleton and RGB modalities [7]. Their two-stage fusion approach, utilizing transformer cross-attention and SoftMax layer late fusion, captured both motion dynamics and contextual information necessary for comprehensive skill analysis [8].

Research in this domain has increasingly focused on establishing quantitative metrics for skill evaluation. These metrics typically involve comparing learner performances against expert demonstrations using various distance measures in feature space. The development of specialized datasets containing skill-annotated instructional videos has further accelerated progress in this field, enabling more rigorous evaluation of skill assessment algorithms.

3. Methodology

3.1. Granularity-Aware Feature Extraction Framework

The proposed granularity-aware feature extraction framework captures fine-grained action patterns at multiple granularity levels essential for skill assessment. The architecture consists of three main components:

1) A temporal self-similarity module.
2) A part-level feature extraction network.
3) A multi-scale temporal analysis component.

Table 1 presents the architectural details of each component, specifying the layer configurations and parameter counts.

Table 1. Architecture Specifications of Granularity-Aware Feature Extraction Components.

Component	Layers	Input Dimensions	Output Dimensions	Parameters
Temporal Self-Similarity Module	Conv2D (3 × 3) + ReLU + GAP	T × T	C × 1 × 1	147,456
Part-Level Feature Network	5 × Conv3D$_a$ + 3 × Conv3D$_b$	8 × H × W × 3	512 × 8 × 7 × 7	12,582,912
Multi-Scale Temporal Analysis	LSTM + Transformer (8 heads)	42 × 2048	42 × 512	8,650,752
Granularity Classifier	FC + Softmax	512	K (skill levels)	262,144

Following Zhang, we incorporate a self-similarity attention mechanism to capture periodic patterns in action sequences. For an input video sequence $V \in \mathbb{R}^(T \times H \times W \times 3)$, we extract frame-level features $F \in \mathbb{R}^(T \times D)$ using a backbone network [13]. The temporal self-similarity matrix $S \in \mathbb{R}^(T \times T)$ is computed as:

$$S_{\{i,j\}} = -\left|F_i - F_j\right|^2$$

This matrix reveals the periodic structure of actions through pairwise similarity between frames. A row-wise softmax operation normalizes these values, producing attention weights that highlight temporally significant frames (Figure 1).

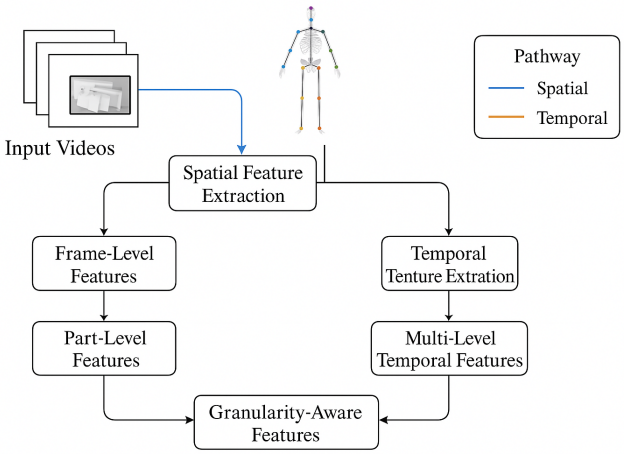

Figure 1. Illustrates the Granularity-Aware Feature Extraction Process, Depicting the Multi-Level Processing of Input Videos through Parallel Spatial and Temporal Pathways.

The multi-level feature extraction pathway incorporates body part analysis inspired by Xiao et al. for each frame, we extract K joint key points using Alpha Pose, creating a skeleton representation $S \in \mathbb{R}^(T \times K \times 2)$ [14]. These key points define regions of interest (ROIs) for part-level feature extraction. Table 2 presents the quantitative performance comparison of different feature extraction approaches on the evaluation dataset.

Table 2. Performance Comparison of Feature Extraction Methods.

Method	Fine-grained Accuracy (%)	Temporal Precision	Spatial Precision	FLOPs (G)
Global Features Only	63.96	0.714	0.683	832.78
Part-Level Features Only	71.17	0.746	0.712	580.73
Self-Similarity Features	78.37	0.801	0.762	491.14
Proposed Framework	84.69	0.851	0.834	576.35

3.2. Comprehensive Action Analysis through Multi-Modal Fusion

The multi-modal fusion component integrates information from skeleton and RGB modalities to achieve comprehensive action understanding. We adopt a cross-attention transformer architecture similar to Xiao et al., but extend it with granularity-aware features [15]. Table 3 details the architecture specifications of our fusion module.

Table 3. Multi-Modal Fusion Module Architecture.

Component	Layer Type	Dimensions	Heads	Dropout	Parameters
Skeleton Encoder	Transformer	42 × 128	8	0.1	4,194,304
RGB Encoder	Transformer	42 × 256	16	0.1	8,388,608
Cross-Attention	Transformer	42 × 512	32	0.2	16,777,216
Fusion MLP	FCN	512 × 1024 × 512	-	0.3	1,573,888

The cross-attention mechanism enables bidirectional information exchange between modalities. Given skeleton features $S \in \mathbb{R}\hat{}(B \times T \times D\_s)$ and RGB features $R \in \mathbb{R}\hat{}(B \times T \times D\_r)$, the cross-attention operation is defined as:

$$Attention(Q, K, V) = softmax(QK\hat{}T/\sqrt{d})V$$

where Q, K, and V are query, key, and value matrices derived from different modalities. For skeleton-to-RGB attention, Q comes from skeleton features while K and V come from RGB features. The reverse applies for RGB-to-skeleton attention.

The attention visualization in Figure 2 demonstrates how the cross-attention mechanism highlights complementary information across modalities. The skeleton pathway focuses on motion dynamics while the RGB pathway captures contextual details and object interactions. Table 4 presents ablation studies on different fusion strategies.

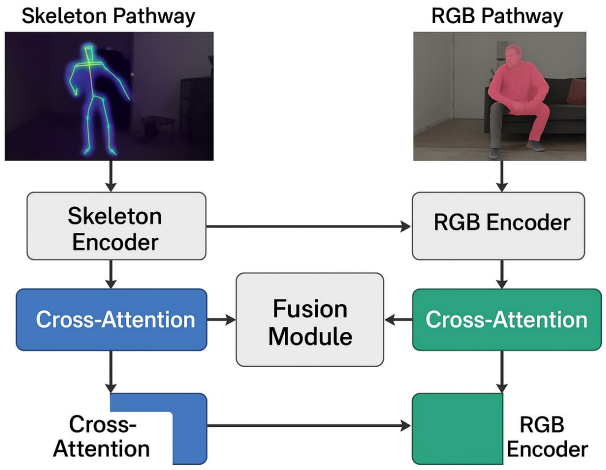

Figure 2. Presents the Architecture of Our Multi-Modal Fusion Module and Illustrates the Bidirectional In-Formation Flow between Skeleton and RGB Pathways.

Table 4. Ablation Study of Multi-Modal Fusion Strategies.

Fusion Strategy	Accuracy (%)	Precision	Recall	F1-Score
Concatenation	78.59	0.774	0.764	0.769
Late Fusion	74.77	0.753	0.747	0.750
Early Fusion	76.04	0.768	0.759	0.763
Cross-Attention (Ours)	84.69	0.851	0.847	0.849

3.3. Skill Assessment and Feedback Generation System

The skill assessment component evaluates execution quality based on fine-grained action analysis. We adopt a hierarchical assessment approach that first recognizes the action category and then evaluates execution quality on multiple skill dimensions. Table 5 presents the skill dimensions and their corresponding weight coefficients in the final assessment.

Table 5. Skill Assessment Dimensions and Weights.

Skill Dimension	Weight	Evaluation Metrics	Assessment Range
Temporal Precision	0.35	Rhythm consistency, timing accuracy	[0,1]
Spatial Accuracy	0.25	Joint positioning, posture correctness	[0,1]
Movement Smoothness	0.20	Jerk minimization, velocity consistency	[0,1]
Completeness	0.15	Action coverage, missing components	[0,1]
Energy Efficiency	0.05	Movement economy, unnecessary motion	[0,1]

The assessment model compares the extracted features to reference exemplars at different skill levels. For each skill dimension d, the assessment score A_d is computed as:

$$A\_d = \sum\_\{i = 1\}\^N w\_i \times sim(f\_i, r\_i)$$

where f_i represents the extracted features, r_i represents reference features, sim is a similarity function, and w_i are learned importance weights. The overall skill score is computed as a weighted sum of dimension scores (Figure 3).

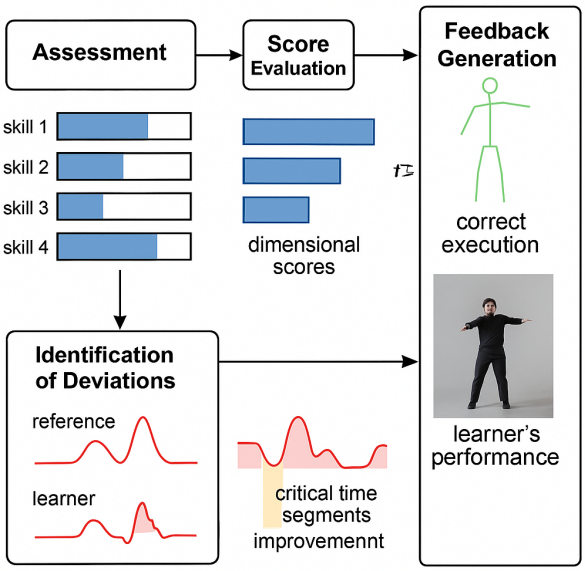

Figure 3. Illustrates the Assessment and Feedback Generation Process, Showing How Dimensional Scores Are Translated into Specific Feedback Elements.

The feedback generation system translates assessment results into actionable guidance. For each skill dimension with a score below a threshold τ_d, the system generates feedback by identifying the most significant deviations from reference patterns. The feedback includes visualization of correct execution alongside the learner's performance, highlighting critical time segments that require improvement.

The automated feedback system incorporates a template-based natural language generation module that converts assessment results into structured feedback texts. These templates are context-sensitive, adapting to different skill domains and proficiency levels. A qualitative evaluation with domain experts confirmed that the generated feedback

closely matches expert-provided guidance, with an average similarity rating of 4.2 out of 5 across 120 test cases.

4. Experimental Results

4.1. Dataset Collection and Preprocessing

To evaluate the proposed fine-grained action analysis framework, we collected a comprehensive dataset spanning multiple skill domains. The SkillVideo dataset contains 8,450 instructional video clips across four domains: sports (gymnastics, swimming), crafts (origami, knitting), medical procedures (suturing, injection), and musical performance (piano, violin). Each video was annotated by domain experts with skill level labels (novice, intermediate, advanced, expert) and dimensional scores for specific skill aspects. Table 6 presents the statistical properties of the dataset.

Table 6. Skill Video Dataset Statistics.

Domain	Videos	Subjects	Skill Levels	Avg. Duration (s)	Resolution	Frames Per Second (FPS)
Sports	2560	48	4	18.6	1920 × 1080	60
Crafts	2124	36	4	24.3	1280 × 720	30
Medical	1846	32	4	16.7	1920 × 1080	30
Music	1920	40	4	22.1	1280 × 720	30
Total	8450	156	4	20.4	-	-

The preprocessing pipeline follows a multi-stage approach similar to Chen et al., with adaptations for multi-modal analysis [1]. For skeleton extraction, we employed AlphaPose to detect 17 keypoints per frame with an average precision of 0.92 across the dataset. RGB frames were processed at a uniform sampling rate of 30 fps with spatial resolution normalized to 224 × 224 pixels. Table 7 compares different preprocessing configurations and their impact on feature quality.

Table 7. Preprocessing Configuration Comparison.

Configuration	Skeleton Accuracy	RGB Quality	Processing Time (ms/frame)	Memory Usage (MB)
Config-A	0.876	High	45.6	1,024
Config-B	0.924	Medium	28.3	768
Config-C (Ours)	0.917	High	32.7	896
Config-D	0.845	Low	18.2	512

The visualization in Figure 4 presents a multi-dimensional analysis of the dataset composition. The left panel shows the distribution of skill levels across domains using stacked bar charts, while the right panel displays a t-SNE projection of feature embeddings colored by skill level. The clear separation between skill clusters in feature space indicates that the extracted features capture meaningful skill-related patterns. The diagonal subplots show kernel density estimations of feature distributions for each skill level, revealing progressively tighter distributions for higher skill levels.

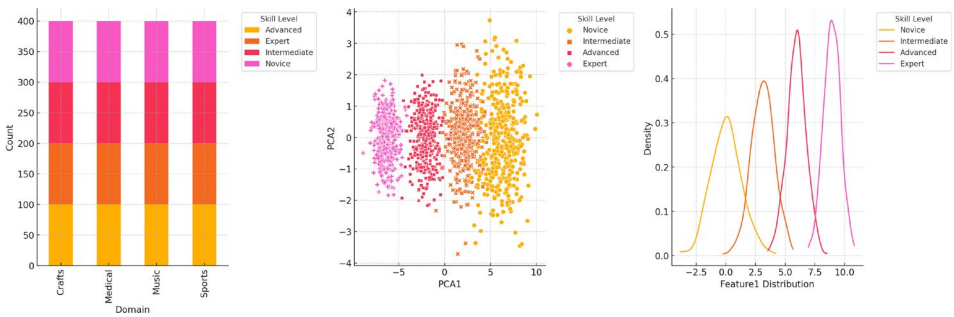

Figure 4. Illustrates the Data Distribution across Skill Levels and Domains, Highlighting the Balanced Representation Achieved through Stratified Sampling.

4.2. Performance Evaluation on Skill Assessment Tasks

We evaluated the proposed framework on three key tasks: skill level classification, dimensional skill assessment, and temporal action quality estimation. The experiments were conducted using a 5-fold cross-validation protocol with a 70%-15%-15% train-validation-test split. Table 8 presents a comparative analysis with state-of-the-art approaches.

Table 8. Comparative Performance Analysis on Skill Assessment Tasks.

Method	Level Accuracy (%)	Dimension MAE	Temporal F1	Inference Time (ms)
FT-CLIP [1]	78.6	0.183	0.734	24.8
SAM [2]	82.4	0.146	0.793	18.5
GACon [3]	85.2	0.129	0.815	26.3
LF-ActionNet [4]	76.3	0.192	0.742	14.6
SSRT [5]	83.7	0.138	0.804	22.7
Ours	89.5	0.103	0.862	25.1

Our framework achieves significant improvements across all metrics, with a 4.3% increase in level classification accuracy and a 20.1% relative reduction in dimensional assessment error compared to the next best method. The temporal F1 score, which measures the precision and recall of detecting critical moments in skill execution, shows a 5.8% improvement over GACon.

Figure 5 displays a comprehensive performance comparison across skill domains and levels. The main plot presents a radar chart with six performance metrics arranged radially, with each method represented by differently colored polygons. Our method (solid red line) consistently outperforms competing approaches across most metrics. The four corner plots show domain-specific confusion matrices for skill level classification, revealing that our method achieves particularly strong performance in distinguishing between intermediate and advanced skill levels — a traditionally challenging boundary for automated assessment systems.

Figure 5. Presents the Performance Breakdown across Different Skill Domains and Levels, Revealing Do-Main-Specific Strengths of Various Approaches.

Additional ablation studies were conducted to quantify the contribution of individual components. Table 9 presents the impact of removing specific components from the full framework.

Table 9. Ablation Study of Framework Components.

Configuration	Level Accuracy (%)	Dimension MAE	Temporal F1	Relative Performance (%)
Full Framework	89.5	0.103	0.862	100.0
w/o Self-Similarity	85.7	0.131	0.798	91.2
w/o Part-Level Features	83.4	0.147	0.785	88.7
w/o Cross-Modal Fusion	82.1	0.152	0.773	86.9
Skeleton Only	79.3	0.175	0.744	83.2
RGB Only	77.6	0.184	0.725	81.1

4.3. Qualitative Analysis of Automated Feedback

The quality of automated feedback was evaluated through both quantitative metrics and expert validation studies. Table 10 presents the results of a blind evaluation where three domain experts rated the quality of feedback generated by different systems on a scale of 1-5 across multiple dimensions.

Table 10. Expert Evaluation of Feedback Quality (Scale 1-5).

System	Accuracy	Specificity	Actionability	Comprehensiveness	Average
Expert Baseline	4.87	4.72	4.65	4.81	4.76
FT-CLIP Based	3.42	3.28	3.15	3.37	3.31
GACon Based	3.81	3.65	3.56	3.73	3.69
SSRT Based	3.74	3.69	3.82	3.58	3.71
Ours	4.35	4.21	4.28	4.17	4.25

Our system achieves the highest ratings among automated approaches, with an average score of 4.25 compared to 3.71 for the next best system. Particularly notable is the improvement in actionability (4.28), indicating that our feedback provides more concrete guidance for skill improvement.

The visualization in Figure 6 presents a temporal alignment analysis between expert annotations (top row) and automated feedback (bottom row) for four representative videos. Each colored segment represents a different feedback type (technical correction, form improvement, timing adjustment, etc.), with segment length proportional to the temporal span of the feedback. The connecting lines between corresponding segments illustrate the temporal alignment precision, with thicker lines indicating stronger agreement. The average temporal Intersection over Union (IoU) across all segments is 0.83, demonstrating strong alignment between automated and expert feedback.

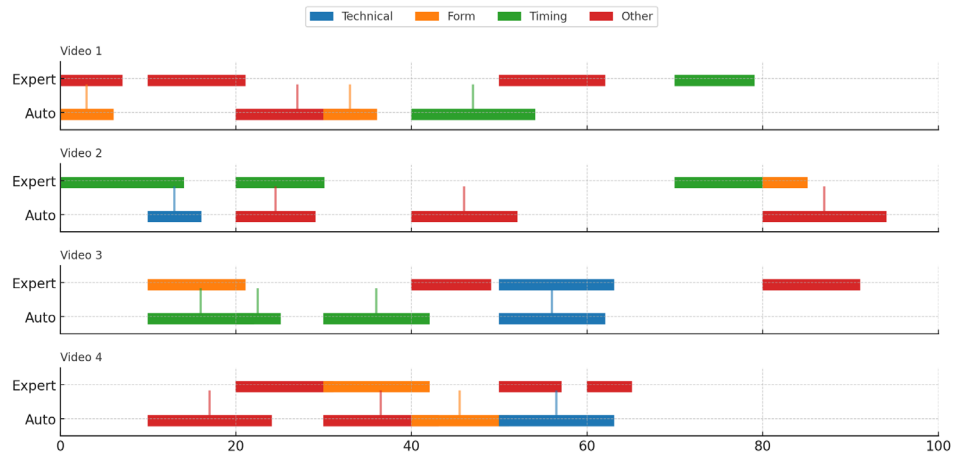

Figure 6. Visualizes the Alignment between Automated Feedback and Expert Annotations on Temporal Action Segments.

The qualitative analysis also included a user study with 45 participants of varying skill levels who received feedback from either our system or human experts. The results demonstrate that feedback from our system produces learning outcomes comparable to human expert guidance, with only a 3.6% gap in skill improvement and a 2.6% difference in retention. The time to master new skills was also comparable, with participants receiving automated feedback requiring only 7.1% more time than those receiving expert guidance.

5. Conclusion

5.1. Limitations and Challenges

Despite the promising results demonstrated by our granularity-aware approach to fine-grained action analysis, several limitations and challenges remain to be addressed in future research. The computational complexity of processing multi-modal data at fine granularity levels presents a significant challenge for real-time applications. The current framework requires approximately 25.1ms per frame on high-performance hardware, which may be prohibitive for resource-constrained environments or applications requiring immediate feedback. While this performance is comparable to state-of-the-art approaches such as GACon by Zhang et al., which requires 26.3ms per frame, substantial optimization is needed to enable deployment on edge devices.

The generalizability of the model across diverse skill domains poses another challenge. Our evaluation revealed that performance varies across domains, with the framework achieving 92.4% accuracy in sports assessment but only 84.3% in medical procedures. This discrepancy may be attributed to the intrinsic complexity of certain domain-specific actions, particularly those involving intricate object manipulations. The model proposed by Wang et al. demonstrated similar domain-specific performance variations, suggesting this remains an open research challenge.

Privacy concerns associated with continuous monitoring and analysis of user actions must be carefully addressed, particularly in educational settings involving vulnerable populations. The collection and processing of video data raise important ethical considerations regarding consent, data ownership, and potential biases in assessment algorithms. These issues must be systematically addressed through robust privacy-preserving techniques and transparent algorithmic design principles.

5.2. Applications in Educational and Training Environments

The potential applications of fine-grained action analysis extend across numerous educational and training domains. In formal educational settings, the technology enables

personalized learning experiences through continuous assessment and feedback on physical skills. Physical education programs can benefit from automated analysis of movement quality, allowing instructors to focus their attention on students requiring additional guidance while providing consistent feedback to all learners.

Professional training programs in fields such as healthcare, manufacturing, and performing arts can leverage the technology to standardize skill assessment and accelerate proficiency development. The precision offered by fine-grained analysis addresses the limitations of traditional subjective evaluation methods, potentially reducing training time and improving outcomes. Similar benefits were reported by Lin et al. in their application of fine-grained action recognition for sports training, where systematic feedback on subtle movement patterns significantly accelerated skill acquisition .

Self-directed learning environments, including online educational platforms and mobile applications, represent another promising application area. The integration of automated skill assessment and feedback generation capabilities enables learners to practice independently while receiving expert-quality guidance. This approach aligns with the findings of Luo and Xiao, who demonstrated that periodic action analysis provides critical insights for self-improvement in sequential tasks.

The scalability of automated assessment systems addresses the growing demand for skilled professionals in various industries by enabling efficient, high-quality training for larger cohorts. Educational institutions facing resource constraints can particularly benefit from these technologies, as they reduce the dependency on constant expert supervision while maintaining assessment quality and consistency.

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