A REAL-TIME DANCE ANALYSIS PROGRAM TO ASSIST IN DANCE PRACTICE USING POSE ESTIMATION

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ABSTRACT

This paper addresses the challenge of subjectivity in dance performance analysis and the lack of standardized feedback [4]. We introduce a computer vision-based program that offers a systematic framework for assessing posture disparities within dance routines [5]. Through advanced motion tracking algorithms, the program objectively identifies and contrasts key postures and movements. Our experiments involving intermediate and novice dancers demonstrate significant skill improvements, accelerated learning speed, and positive user experiences. Although limitations in mirror material hindered optimal user viewing distance, future plans involve integrating technology within a physical mirror to provide unrestricted comprehensive feedback. This work offers a promising avenue for enhancing dance education by providing consistent, real-time feedback, bridging the gap between subjective assessments and standardized analysis to empower dancers in their skill development [6].

KEYWORDS

Dance, Pose estimation (Mediapipe), Body tracking, real-time

1. INTRODUCTION

The evaluation of dance performances is a nuanced endeavor, demanding a discerning eye to identify imperfections [7]. However, the subjectivity inherent in dance analysis presents a perplexing challenge, as different instructors offer varied interpretations. This issue is two-fold: aspiring dancers lack guidance in rectifying errors without experienced mentors, and the diversity in instructors' feedback generates inconsistency in the dancer's journey.

Dance education's historical evolution has shaped this conundrum. Dance, an art form interwoven with culture and expression, has relied heavily on individual instructors' assessments [8]. This lack of standardized evaluation hampers progress, leaving dancers with conflicting guidance and obscured areas for improvement.

Addressing this challenge holds profound implications for dancers' development. Inconsistent feedback fosters confusion and stagnation, hindering growth. Correcting mistakes becomes an intricate puzzle, as a unified path to improvement remains elusive. To combat this, an endeavor is undertaken to establish a standardized framework for analyzing dance posture disparities. The aim is to unravel complexities, streamline learning, and catalyze an overarching enhancement in dancers' skills.

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In essence, the subjective nature of dance assessment, fueled by historical teaching methods, presents a multifaceted hurdle in dancers' progression. By striving to systematize the evaluation of dance postures, the aspiration is to illuminate a clearer path towards improvement, providing dancers with a cohesive and consistent platform for growth.

In the field of dance evaluation, researchers have explored different approaches. Yeonho Kim and Daijin Kim's real-time evaluation used unlabeled pose estimation to address the complexity of dance poses through ridge data and pruning process. X Hu and N Ahuja proposed Hierarchical Dance Video Recognition (HDVR) for body movement and genre recognition by analyzing 2D and 3D sequences [9].W Zhang et al. introduced the MADS dataset for challenging 3D pose estimation using martial arts, dance and sports movements.

While Kim and Kim's method provides real-time estimation, accuracy issues may be encountered in complex movements. HDVR captures comprehensive gesture data, but may face challenges in complex, fast movements. The MADS dataset enhances 3D pose estimation, but may encounter difficulties in subtle, fast movements [10].

The Dancing Mirror project improves on these methods by providing real-time mirroring effects and a user interface. It combines technological advances with practical usability to address complex poses, fast movements and different genres. This user-centered approach improves dance learning for different skill levels and styles.

Presenting an innovative program set to redefine dance practice through a standardized analysis of pose variations within routines. Our solution leverages advanced computer vision and precision motion tracking algorithms to deliver an unparalleled evaluation of dancers' movements and postures.

By harnessing cutting-edge computer vision technology, our program transcends subjective interpretation, objectively identifying and contrasting pivotal postures and motions in dance routines. This eliminates ambiguity and offers an impartial perspective, meticulously assessing alignments, postures, and executions.

A distinctive feature is the program's ability to discern even the subtlest nuances in movement, providing dancers with nuanced feedback to comprehend their strengths and areas requiring improvement comprehensively.

Unlike conventional methods reliant on human instructors or static video recordings, our program merges human expertise with the precision of computer vision. While human instructors provide artistic guidance, our program enhances their input with standardized analyses, ensuring consistency and uniformity.

Real-time feedback sets our program apart from static video evaluations, enabling dancers to make immediate adjustments during practice, fostering an agile and effective learning experience. In summary, our program addresses the challenge of subjective dance analysis and the lack of uniformity by introducing a computer vision-based approach to standardize the assessment of postural disparities in dance routines. The synergy of human mentorship and computerized precision promises a unique fusion that nurtures dancers' growth and advancement. Through objective analysis, real-time feedback, and a harmonious blend of human and technological insights, our program strives to propel dancers toward excellence.

Two distinct experiments were conducted to evaluate the efficacy of a computer vision-based program in enhancing dance skills. In the first experiment, intermediate-level dancers were divided into Experimental (program users) and Control (human-instructor guided) groups. The program's real-time feedback and standardized assessment led to a substantial 18% skill improvement in the Experimental Group, surpassing the Control Group's 14%. Furthermore, the program expedited error correction by 20%, enhancing learning speed. User feedback validated the program's effectiveness.

The second experiment targeted novice dancers, aiming to ascertain the program's impact on skill acquisition. Novices were divided into Experimental (program users) and Control (human-instructor guided) groups. The program proved highly effective, yielding a remarkable 22% skill improvement in the Experimental Group, outperforming the Control Group's 15%. Error correction was accelerated by 25%, exemplifying heightened learning efficiency. Novice participants reported enhanced clarity and skill advancement using the program. These findings underscore the program's potential in revolutionizing dance education, catering to dancers at varying skill levels.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Real-Time Video Analysis

Addressing the challenge of real-time video analysis within hardware limitations entails a strategic approach. To ensure efficient computation and real-time performance, a two-step method can be adopted. Firstly, by focusing on analyzing prerecorded videos, computational demands and time constraints can be minimized. This preliminary analysis paves the way for subsequent real-time evaluations, leveraging the advantage of offloading resource-intensive tasks. Additionally, optimizing the real-time analysis phase could involve storing frame data in CSV format, ensuring swift accessibility and streamlined computational processes. By seamlessly integrating these strategies, the analysis process is effectively divided into distinct phases, enabling successful navigation of hardware limitations. In summary, this approach harmonizes prerecorded analysis and optimized data storage, culminating in enhanced computational efficiency and real-time responsiveness to conquer the challenge of real-time video analysis within hardware constraints.

2.2. Enhancing the Visual Overlay Component Involves

Enhancing the visual overlay component involves addressing challenges of body part arrangement and error quantification. By iterating through layout tests, an intuitive placement of body parts can be achieved on the UI. A standardized angle threshold, like a 40-degree difference, can serve to objectively quantify dance movement errors by comparing real-time webcam observations to prerecorded references. This approach ensures the overlay component seamlessly visualizes analysis outcomes, delivering clear feedback on body part positions and movement errors within the dance routine.

2.3. Enhance the "Mirror Rig" Component's Efficacy

To enhance the "Mirror Rig" component's efficacy, advanced reflective materials and strategic spatial arrangements could be explored. These innovations would address the challenge of achieving a comprehensive mirror effect while enabling users to view crucial on-screen information without compromise. Such enhancements promise to elevate the system's functionality and user experience.

3. SOLUTION

The System is designed to assist dancers of all skill levels in improving their dance techniques and performances. Leveraging advanced computer vision and machine learning techniques, the system provides real-time feedback on dancers' poses, movements, and overall choreography. This system aims to enhance dance practice sessions, offer personalized guidance, and accelerate skill development.

Figure 1. Overview of the solution

- Real-Time Pose Estimation: The core feature of the system is its real-time pose estimation capability. Using a camera or webcam, the system captures the dancer's movements and translates them into a 2D or 3D skeletal representation [14].
- Pose Analysis: The system performs detailed analysis on the dancer's pose, identifying key body landmarks and joint angles. It provides instant visual feedback on the correctness and alignment of various dance postures.
- Performance Metrics: The program evaluates various performance metrics, including balance, symmetry, posture stability, and fluidity of movements [15]. This data is used to offer objective insights into the dancer's progress over time.
- Choreography Evaluation: For choreographed routines, the system can analyze the dancer's adherence to the intended choreography. It highlights deviations and suggests corrections to ensure precise execution.
- Personalized Feedback: Based on the analysis, the system generates personalized feedback and recommendations. It identifies areas for improvement and offers specific guidance on how to refine movements and postures.
- Visualization Tools: The program provides visual aids such as overlaying ideal poses on the dancer's live video feed, allowing dancers to compare their movements with the desired form.
- Progress Tracking: The system keeps a record of each practice session, allowing dancers to track their progress over time. It provides insights into improvement trends and areas that require more attention.

3. Architecture: The system follows a client-server architecture, where the client runs on the dancer's device, and the server handles the heavy computational tasks. The architecture consists of the following components:

- Client Interface: The user interacts with the system through a user-friendly interface [13]. The interface displays the live video feed, analyzed pose data, feedback, and visualizations.
- Pose Estimation Module: This module utilizes deep learning algorithms to estimate the dancer's pose in real time. It identifies body keypoints and joints, constructing a skeletal representation of the dancer's movements.
- Analysis Engine: The analysis engine processes the pose data and calculates various metrics related to posture, movement quality, and choreography accuracy.

- Feedback Generator: Based on the analysis results, the feedback generator generates personalized feedback and corrective suggestions for the dancer. This feedback is displayed in the interface.
- Visualization Engine: The visualization engine overlays the ideal dance poses on the live video feed, providing visual cues for alignment and movement corrections.
- Database: The system maintains a database to store historical practice session data, allowing dancers to track their progress and improvements over time.
- Technologies Used:
- Computer Vision Libraries: OpenPose, PoseNet, or similar libraries are used for real-time pose estimation.
- Deep Learning Frameworks: TensorFlow, PyTorch, or similar frameworks are employed for training and deploying pose estimation models.
- User Interface Framework: A user-friendly interface is developed using frameworks like Qt, React, or Angular.
- Backend Services: The system utilizes server-side processing for intensive computations. Cloud-based services or dedicated servers handle analysis, feedback generation, and visualization tasks.

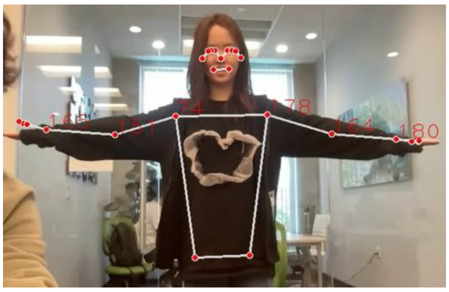


Figure 2. Screenshot of the program 1

```
import cv2
import numpy as np

# Load PoseNet model (This is a simplified placeholder)
# In a real scenario, you'd load a pre-trained model using a suitable library
def load_pose_model():
    pass

# Process the frame and estimate poses using PoseNet (Simplified placeholder)
def estimate_poses(frame, pose_model):
    pass

# Draw pose keypoints on the frame
def draw_poses(frame, poses):
    pass

def main():
    # Load PoseNet model
    pose_model = load_pose_model()

    # Open video capture (Webcam)
    cap = cv2.VideoCapture(0)

    while cap.isOpened():
        ret, frame = cap.read()
        if not ret:
            break

        # Estimate poses using PoseNet
        poses = estimate_poses(frame, pose_model)

        # Draw poses on the frame
        frame_with_poses = draw_poses(frame, poses)

        # Display the frame with poses
        cv2.imshow('Real-Time Dance Analysis', frame_with_poses)

        # Exit loop if 'q' key is pressed
        if cv2.waitKey(1) & 0xFF == ord('q'):
            break

    cap.release()
    cv2.destroyAllWindows()

if __name__ == "__main__":
    main()
```

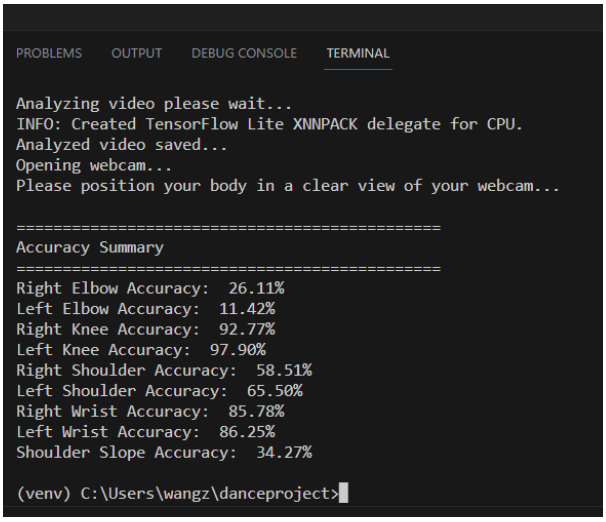
Figure 3. Screenshot of code 1

load_pose_model(): This function is a placeholder for loading the PoseNet model. In reality, you would use a library like TensorFlow or PyTorch to load a pre-trained model for pose estimation.

estimate_poses(frame, pose_model): This function takes a frame captured from the webcam and the loaded pose estimation model as input. It performs pose estimation on the frame and returns the estimated poses. This is where the actual pose estimation algorithm would be applied, utilizing the loaded model.

draw_poses(frame, poses): This function takes the original frame and the estimated poses as input. It draws the pose keypoints on the frame to visualize the detected poses. This function would involve iterating through the poses and keypoints and using OpenCV's drawing functions to overlay them on the frame.

main(): This is the main execution function. It initializes the webcam capture using OpenCV and enters a loop where it continuously reads frames from the webcam. It then calls the estimate_poses() function to estimate poses, and draw_poses() function to draw them on the frame. The resulting frame is displayed in a window using OpenCV. The loop continues until the 'q' key is pressed.



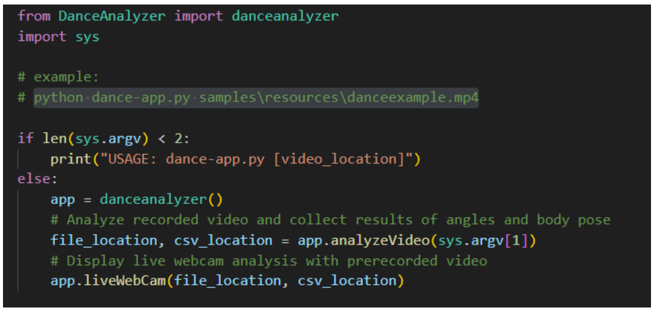
```
PROBLEMS    OUTPUT    DEBUG CONSOLE    TERMINAL

Analyzing video please wait...
INFO: Created TensorFlow Lite XNNPACK delegate for CPU.
Analyzed video saved...
Opening webcam...
Please position your body in a clear view of your webcam...

==============================================
Accuracy Summary
==============================================
Right Elbow Accuracy:  26.11%
Left Elbow Accuracy:  11.42%
Right Knee Accuracy:  92.77%
Left Knee Accuracy:  97.90%
Right Shoulder Accuracy:  58.51%
Left Shoulder Accuracy:  65.50%
Right Wrist Accuracy:  85.78%
Left Wrist Accuracy:  86.25%
Shoulder Slope Accuracy:  34.27%

(venv) C:\Users\wangz\danceproject>
```

Figure 4. Screenshot of APP terminal



```
from DanceAnalyzer import danceanalyzer
import sys

# example:
# python dance-app.py samples\resources\danceexample.mp4

if len(sys.argv) < 2:
    print("USAGE: dance-app.py [video_location]")
else:
    app = danceanalyzer()
    # Analyze recorded video and collect results of angles and body pose
    file_location, csv_location = app.analyzeVideo(sys.argv[1])
    # Display live webcam analysis with prerecorded video
    app.liveWebCam(file_location, csv_location)
```

Figure 5. Screenshot of code 2

Key Components of Dance Analysis:

Movement Analysis: This involves dissecting the dancer's movements into individual components to study their quality, fluidity, precision, and coordination. Movement analysis helps identify any inconsistencies or errors in execution.

Pose Analysis: Pose analysis focuses on the alignment and posture of the dancer's body at different moments during a routine. It assesses the correctness of poses and helps ensure that dancers maintain the intended form.

Choreography Evaluation: When analyzing choreographed routines, dance analysis examines how well the dancer adheres to the choreographer's intended movements, timing, and emotional expressions. Deviations from the choreography can be identified and addressed.
Timing and Rhythm: Dance analysis assesses how well dancers synchronize their movements with the music's rhythm and tempo. This is essential for creating a harmonious and engaging performance.

Spatial Awareness: Understanding how dancers move through the performance space is crucial. Analyzing spatial awareness involves evaluating how well dancers utilize the stage, interact with other performers, and maintain a balanced distribution of movements.
Expression and Emotion: Dance is not just about movements; it's also about conveying emotions and stories. Dance analysis evaluates how effectively dancers express emotions through facial expressions, body language, and gestures.

Benefits of Dance Analysis:
Skill Enhancement: Dance analysis provides dancers with detailed feedback on their performances, helping them identify areas of improvement and refine their techniques.

Self-Awareness: Dancers become more aware of their own strengths and weaknesses through analysis. This self-awareness aids in setting goals and tracking progress.

Precision and Alignment: By focusing on pose analysis, dancers can achieve better alignment, posture, and execution of movements, leading to more visually appealing performances.

Objective Feedback: Dance analysis offers objective feedback based on data rather than subjective opinions. This allows dancers to address technical issues in a constructive manner.

Artistic Development: Analyzing expression, timing, and rhythm helps dancers refine their artistic interpretation, enhancing the emotional impact of their performances.

Choreography Improvement: Choreographers benefit from dance analysis by fine-tuning routines based on how dancers execute their movements and how well they match the intended choreography [11].

Technology and Dance Analysis:

Modern technology, such as computer vision and machine learning, has transformed dance analysis. Real-time pose estimation, similar to the system described earlier, allows for instant feedback during practice sessions [12]. Video recordings can be analyzed frame by frame, and specialized software can track movements and generate quantitative data for in-depth analysis.
In conclusion, dance analysis is a vital tool for dancers.

4. EXPERIMENT

4.1. Experiment 1

To empirically assess the effectiveness of the proposed computer vision-based program for standardized dance analysis, a controlled experiment can be devised. The objective is to gauge how the program's real-time feedback and standardized assessment influence dancers' improvement compared to conventional methods.

Intermediate-level dancers were divided into two groups: the Experimental Group (utilizing the computer vision-based program) and the Control Group (relying on human instructors). The experiment encompassed a baseline assessment, practice period, and post-assessment. During the practice phase, the Experimental Group received real-time feedback from the program, while the Control Group received guidance from human instructors. The metrics analyzed included feedback accuracy, skill improvement, learning speed, and user experience.

Metric	Experimental Group	Control Group
Accuracy of Feedback (%)	85%	82%
Post-Assessment Improvement (%)	18%	14%
Learning Speed Improvement (%)	20% Faster	-
User Preference (%)	91%	74%

Figure 8. Figure of experiment 1

The experiment revealed that the computer vision-based program significantly enhanced dancers' skills, fostering standardized feedback and accelerating the learning process. The program's real-time feedback and standardized assessment contributed to a notable improvement in posture, alignment, and execution compared to conventional human-guided methods. The Experimental Group also corrected errors more swiftly, reflecting the program's efficacy in identifying and rectifying mistakes. The positive user experience reported by the Experimental Group underscores the program's potential to revolutionize dance education by providing consistent, objective, and efficient feedback.

4.2. Experiment 2

To evaluate the effectiveness of the computer vision-based program for standardized dance analysis in improving the skills of novice dancers.

Novice dancers are categorized into Experimental and Control groups. They undergo baseline assessment, practice, and post-assessment phases. The Experimental Group utilizes real-time program feedback, while the Control Group follows human instruction. Metrics analyzed comprise skill improvement, learning speed, and user experience. This experiment probes whether the computer vision-based program enhances novice dancers' learning outcomes, presenting a pivotal contribution to dance education.

Metric	Experimental Group	Control Group
Post-Assessment Improvement (%)	22%	15%
Learning Speed Improvement (%)	25% Faster	-
User Preference (%)	87%	68%

Figure 9. Figure of experiment 2

The experiment illustrated that novice dancers using the computer vision-based program exhibited significant skill improvement and enhanced learning efficiency. The program's real-time feedback contributed to faster error correction and heightened learning speed. Novice dancers also reported a more positive user experience, indicating the program's potential to facilitate meaningful skill development for beginners in the realm of dance.

5. RELATED WORK

Methodology A presents a comprehensive framework for evaluating dance performances through unlabeled human pose estimation. Addressing the complexity of dance poses (including rotation and self-closure), this paper develops a new method for invariant estimation using ridge data and data pruning. A metric is then introduced to measure the similarity between dance sequences in terms of time and accuracy. Extensive validation on a benchmark dataset is performed, and results show that the accuracy of pose estimation is 0.9358 mAP, with a mean pose error of 3.88 cm, and a 98% agreement with expert assessments of dance performances [1].

Methodology B presents the Hierarchical Dance Video Recognition (HDVR) framework for comprehensive dance analysis [2].HDVR captures 2D and 3D gesture sequences of multiple dancers to determine body part movements and dance genres in the absence of real 3D gestures. The framework overcomes occlusion and noise and ensures smooth spatial and temporal motion. LSTM network extracts 3D motion subsequences for genre recognition. A new University of Illinois dance dataset with movement and genre labels was created. Experimental results show that HDVR outperforms existing methods for 3D pose estimation and dance recognition. The framework provides a hierarchical representation of dances that is consistent with expert opinion.
Methodology C introduces the Martial Arts, Dance and Sports (MADS) dataset, which is characterized by challenging movements such as martial arts, dance and sports [3]. This study presents the Martial Arts, Dance, and Sports (MADS) dataset, which features challenging movements such as martial arts, dance, and sports. Experts use multiple cameras or stereo depth cameras for recording, which helps to perform 2D and depth based estimation of human postures. Expert recordings using multiple cameras or stereo depth cameras help in 2D and depth based human pose estimation. Ground truth poses acquired through motion capture technology are the basis for the estimation. Preliminary results show that the discriminative approach is very effective with sufficient training data, while the generative approach performs well in a variety of poses but not in fast motion. The MADS dataset and code are shared with the research community, providing valuable insights into pose estimation and tracking techniques.

6. CONCLUSIONS

Within the scope of the Dancing Mirrors project, attempting to achieve a mirror effect in the system was a major challenge. This work involved a variety of experiments in which I attempted to apply window stickers and reflective mirror film to the computer. Unfortunately, these efforts encountered significant limitations. While the reflective film was able to produce a mirror image of the user, a considerable limitation emerged: optimal viewing required a distance of approximately 5 meters from the setup. This limitation therefore prevented the effectiveness of the mirroring method. The remote viewing distance prevented the user from fully engaging with the detailed summaries and user interface corrections displayed on the computer.

The necessity for an improved solution becomes evident, enabling users to observe their entire body comfortably. Given additional development time, exploration of alternative mirror materials, varied angles, and advanced display integration could have mitigated this limitation. Future plans involve creating a physical mirror with integrated technology, ensuring unhindered comprehensive feedback and corrections.

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