Logic-Ca: A Fuzzy Logic-Based Framework for Enhancing the Camera Angles and the Field of View in Traditional Dance Documentation

Nugrahardi Ramadhani
Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
dhanisoenyoto@its.ac.id

Didit Prasetyo
Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
didit@its.ac.id

Ary Mazharuddin Shiddiqi
Department of Informatic Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
ary.shiddiqi@its.ac.id

Intan Rizky Mutiaz
Faculty of Art and Design, Institut Teknologi Bandung, Bandung, Indonesia
intanrm@itb.ac.id

Mochamad Hariadi
Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia | Department of Computer Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia
mochar@its.ac.id (corresponding author)

Received: 2 June 2025 | Revised: 2 July 2025 and 10 July 2025 | Accepted: 11 July 2025

ABSTRACT

This study presented a fuzzy logic framework to optimize the camera angles and Field of View (FOV) in the documentation of Indonesian traditional dances, specifically the Remo dance. The system utilized BioVision Hierarchy (BVH) Motion Capture (MoCap) data to dynamically modify the camera settings according to movement characteristics, such as velocity and spatial complexity. The framework incorporated five camera perspectives (eye level, low angle, high angle, frog angle, bird's eye) and three classes of FOV (narrow, medium, wide). The results indicated that a low angle with a narrow FOV most effectively captured the dramatic hand motions, whereas an eye level perspective with a medium FOV was appropriate for the neutral transitions. Validation by five specialists in dance and five in cinematography resulted in a Mean Opinion Score (MOS) of 79%, affirming the system's conformity with the conventional dance philosophy. The current approach decreased the manufacturing time by 25% and enhanced the adjustment precision compared to traditional methods. Future work will broaden the validation to additional dancing styles and integrate machine learning for improved accuracy.

Keywords-traditional dance documentation; fuzzy logic; motion capture; camera angle; field of view; cultural preservation

I. INTRODUCTION

Traditional dance conveys cultural meaning, life rhythm, and artistic beauty in every civilization. The complexity of movement, visual composition, and aesthetic aim should be captured using modern approaches. For instance, proper lighting generates a cinematic tone and mood to assist the above efforts [1].

MoCap has become a standard tool for recording the details of human movements with precision. Authors in [2] noted that MoCap allowed an exact body movement analysis, making it suitable for capturing traditional dances. In [3, 4], it was revealed that MoCap could digitize dance motions, although it lacked in cinematographic principles, which generally enrich the dance's visual storytelling. MoCap has also been combined with virtual reality to allow global audiences to explore dance performances in immersive virtual spaces [5]. To support the motion analysis, authors in [6] promoted the BVH format for kinematic assessment and cultural preservation.

Cinematographic research has shown that camera techniques significantly influence viewers' emotional engagement. According to [7], the camera angles substantially altered the emotional interpretation and visual scene appeal. Similarly, authors in [8] indicated that the intricacy of motion and range of vision enhanced viewers' aesthetic experience. Authors in [9, 10] stressed the narrative role of camera placement and focus. Authors in [11] further claimed that the aesthetic value of dance was tied to the complexity of movement kinematics. Despite these insights, there are few studies exploring the adaptive cinematographic approaches that respond to dynamic dance motions.

Fuzzy logic has been applied to a wide range of motion-based control systems, including robotic arms, linear motion platforms, and pneumatic piston systems [12-14]. It is especially well-suited to handling uncertain or imprecise data, such as those found in human motion analysis [15]. In animation, fuzzy logic has been employed to automate the camera angle selection and director-style profiling [16], and it has proven effective for ergonomics and motion optimization [17]. However, its integration with cultural and artistic criteria required for documenting traditional dance is limited. Additional work has focused on enhancing MoCap with frameworks, like MoCap Markup Language, and systems for personalized style translation in animation [18, 19], while fuzzy logic has also been used to increase the realism in facial expressions and body gestures [20].

In response to these gaps, this research proposes a MoCap, fuzzy logic, and an adaptive cinematography methodology for high-fidelity traditional dance documentation. Specifically, the current approach utilizes fuzzy logic to make real-time camera angle and FOV decisions through BVH motion data, movement velocity, and spatial complexity.

II. RESEARCH METHODOLOGY

The motion of a dancer is represented as a time series of 3D joint coordinates obtained from BVH MoCap data. From this, two key parameters can be derived:

- Velocity of a body part between two-time steps:

$$v_t = \frac{\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}}{\Delta t} \tag{1}$$

- Spatial complexity over a window of n frames:

$$C = \sum_{i=1}^{n} \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2 + (\Delta z_i)^2} \tag{2}$$

These factors are used as inputs for the fuzzy logic system $\mathcal{F}$, which outputs the optimal camera configuration parameters as:

$$\mathcal{F}(v, C) \rightarrow (\theta, \phi), \tag{3}$$

$$\theta \in \{0°, 30°, 60°, 90°, 120°\},$$

$$\phi \in \{45°, 75°, 105°\},$$

where θ denotes the camera angle (eye level, low angle, high angle, frog angle, bird's eye) and ϕ represents the FOV (narrow, medium, wide).

The objective of this research was to develop an adaptive cinematographic system that selects the optimal camera angle θ and FOV ϕ for each motion segment based on real-time analysis of v and C. The system aimed to:

- Maximize the visual clarity and esthetic expression for both the dramatic and transitional movements,
- Minimize the manual configuration effort and production time,
- Preserve the cultural meaning through appropriate framing and composition.

The maximum MOS was calculated across m expert evaluations:

$$\max_{\mathcal{F}} \text{MOS} = \frac{1}{m} \sum_{j=1}^{m} \text{Score}_j(\theta, \phi \mid v, C) \tag{4}$$

subject to the following constraints:

$$\theta, \phi \in Distinct\ Configurations \tag{5}$$

$$v, C \in R_{\geq 0} \tag{6}$$

The methodology of this study is illustrated in Figure 1, and the algorithm used is presented in Figure 2. The following key stages are involved:

- MoCap was performed on traditional Indonesian Remo dance, known for its symbolic hand gestures and synchronized body emotions. The data, which were recorded in BVH format, contain non-public sequences and are available upon request under data sharing agreements.
- From the BVH data, the velocity and spatial complexity values were computed using (1) and (2), respectively. The velocity parameter quantified the rate of positional change between two consecutive frames, while the spatial complexity measured the cumulative displacement across 3D space, reflecting the intricacy of the dancer's movements.
- The development of a fuzzy logic system was designed to interpret the motion parameters into cinematographic recommendations, specifically, camera angles and FOV. The system translated movement characteristics, such as velocity and spatial complexity, into appropriate visual framing strategies.

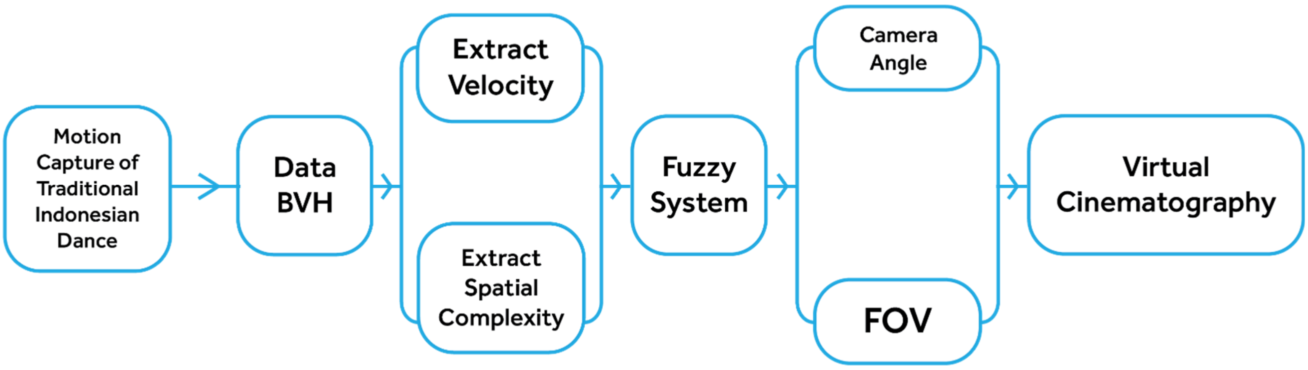


Fig. 1. The research methodology of the fuzzy logic-based system on traditional Indonesian dance MoCap.

Algorithm 1 Motion-Guided Cinematographic Recommendations using Fuzzy Logic

Input: BVH motion capture data $\mathcal{D}$ from Remo dance

Output: Recommended camera angle θ and field of view ϕ

Phase 1: Data Acquisition and Preprocessing

The load BVH file $\mathcal{D}$

Extract 3D joint coordinates $\{(x_t, y_t, z_t)\}$ for each bone over time

Phase 2: Motion Parameter Computation

for each frame $t = 1$ to $T - 1$ **do**

Compute velocity v_t using:

$$v_t = \frac{\sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2 + (z_{t+1} - z_t)^2}}{\Delta t}$$

end for

for each frame window of size n **do**

The spatial complexity C as

$$C = \sum_{i=1}^{n} \sqrt{(\Delta x_i)^2 + (\Delta y_i)^2 + (\Delta z_i)^2}$$

end for

Phase 3: Fuzzy Logic Inference

Define fuzzy sets for velocity and spatial complexity: {Low, Medium, High}

The fuzzy rule mapping is defined $(v, C) \rightarrow (\theta, \phi)$

for each frame window

Fuzzify v and C

Apply fuzzy inference to derive (θ, ϕ)

Defuzzify to obtain crisp camera angle θ and FOV ϕ

end for

return Sequence of (θ, ϕ) for visual documentation

Fig. 2. Algorithm 1 used for the caluclation of velocity and spatial complexity.

The camera angle classifications included:

- frog eye (an extremely low-angle shot positioned beneath the subject)
- eye level (aligned with the subject's eye height)
- high angle (shot from above the subject)
- low angle (shot from below the subject)
- over - the - shoulder (capturing from behind the subject's shoulder)
- bird's eye (a top-down view perpendicular to the ground)
- slanted or Dutch angle (a tilted frame for dynamic visual impact)

The relative positions and perspectives of each angle are displayed in Figure 3.

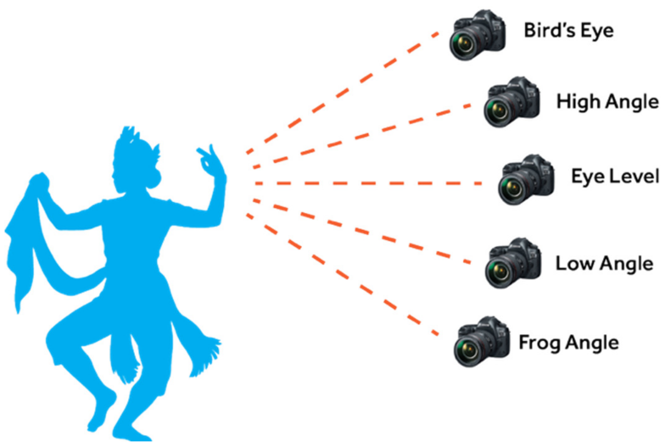


Fig. 3. Cinematographic camera angles: classification.

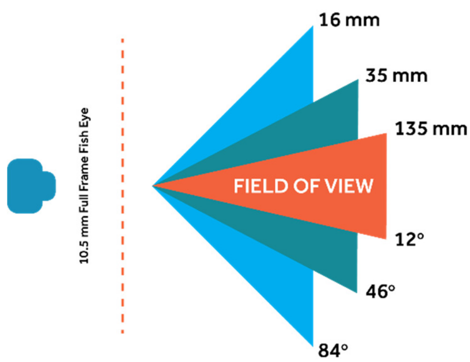


Fig. 4. Camera's FOV.

Similarly, the camera's FOV was categorized into three principal groups (Figure 4):

- narrow (30° - 50°)
- medium (50° - 70°)
- wide (70° - 100°)

These FOV categories are used to determine the visual coverage and depth that are suitable for capturing the expressive nuances and contextual transitions within the dance.

The fuzzy logic system, depicted in Figure 5, began with the definition of membership functions for the input parameters -velocity and spatial complexity- each categorized linguistically as low, medium, or high. A set of fuzzy inference rules was constructed to determine the optimal combination of the camera angle and FOV based on these motion parameters. For instance, if both the velocity and complexity were classified as medium, the system selected an eye-level camera angle with a narrow FOV to emphasize the detailed movement in the most active body segments. Conversely, when both the velocity and complexity were high, a bird's eye angle with a wide FOV was chosen to capture the dancer's overall movement space and spatial patterns.

The system was implemented through simulation using Blender 3D software. BVH MoCap data were processed using a Python script developed to extract the motion parameters and apply fuzzy rules to the virtual camera settings. The camera was programmed to switch dynamically between predefined angles, such as frog eye, high angle, low angle, and eye level, and adjust its FOV in real time according to the movement dynamics at different temporal segments of the Remo dance.

Algorithm 2 Fuzzy Logic-Based Cinematographic Decision System

Input: Motion parameters: velocity v and spatial complexity C

Output: Camera angle θ and field of view ϕ

Step 1: Fuzzification

The linguistic variables for v and C: *Low, Medium, High*

Define membership functions $\mu_v(v)$ and $\mu_C(C)$ for each category.

Step 2: Fuzzy Inference Rules

The rule base of the form is defined as follows:
If v is *Low* and C is *Low* → θ = *Eye Level*, ϕ = *Medium*
If v is *Medium* and C is *Medium* → θ = *Eye Level*, ϕ = *Narrow*
If v is *High* and C is *High* → θ = *Bird's Eye*, ϕ = *Wide*
If v is *High* and C is *Low* → θ = *Frog Angle*, ϕ = *Narrow*
[Additional rules as needed]

Step 3: Inference

The fuzzy rules are evaluated using min–max inference or the Mamdani method.

Combine the output fuzzy sets for θ and ϕ

Step 4: Defuzzification

Apply the centroid or weighted average method to convert fuzzy outputs into crisp values for

$$\theta^* = \text{Defuzzify}(\mu_\theta), \quad \phi^* = \text{Defuzzify}(\mu_\phi)$$

return (θ^*, ϕ^*)

Fig. 5. Algorithm 2.

The outcome was an animated video in which the camera angles and FOV changed responsively to reflect the intensity and characteristics of the dancer's movements. To validate the system, a qualitative assessment was conducted involving five traditional dance experts as well as five cinematography experts. The evaluations were based on three criteria: visual esthetics, cultural representation, and the effectiveness of camera use in communicating the dance's cultural values. A MOS on a scale of 1-10 was utilized to quantify the expert judgments regarding visual quality and philosophical alignment with traditional dance principles. Expert feedback was incorporated to recalibrate the fuzzy rules, thereby enhancing the system's ability to accurately reflect nuanced movement patterns. After recalibration, the outputs of the fuzzy-based animated documentation were compared with conventionally recorded dance videos. This assessment included indicators, such as production time efficiency, visual esthetics, and the system's adaptability to dynamic changes in movement.

III. RESULTS AND DISCUSSION

The analysis of BVH MoCap data for the Remo dance revealed different patterns of skeletal activity across various body parts. As portrayed in Figure 6, the right arm and right-hand joints exhibited high-velocity motion throughout the performance. This continuous activity indicated the upper limbs' primary expressive function in choreographic intent and stylistic nuance, particularly on the right. The left arm and hand joints demonstrated shorter high-velocity movement, suggesting a supportive role in the overall movement. The overlap in high-velocity motion between upper and lower extremities suggested intentional coordination. This synchronicity reflected conscious choreographic planning, as hands and feet are activated together to add rhythmic and expressive complexity to Remo dance.

The spatial complexity analysis, as illustrated in Figure 7, showed how the bones move differently in three dimensions. The right and left arm parts had the highest spatial complexity scores, indicating a lot of dynamic choreography. This complexity arose from sweeping gestures, arm extensions, and stylistic hand positions that traverse various spatial planes. The right forearm, left forearm, and right hand also indicated enhanced complexity, suggesting that these parts contributed to expressive performance. The fine motor articulation, fast transitions, and subtle motions improved the dance's aesthetic elegance.

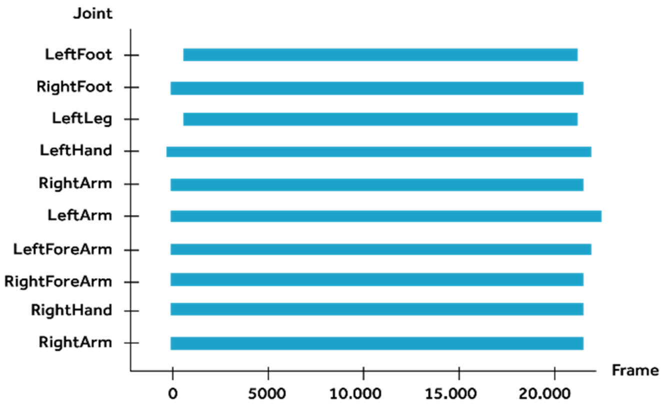


Fig. 6. Top 10 joints with the highest average velocity in the Remo dance based on the BVH MoCap data. The x-axis represents the timeline in frames, indicating sustained movement across various skeletal joints.

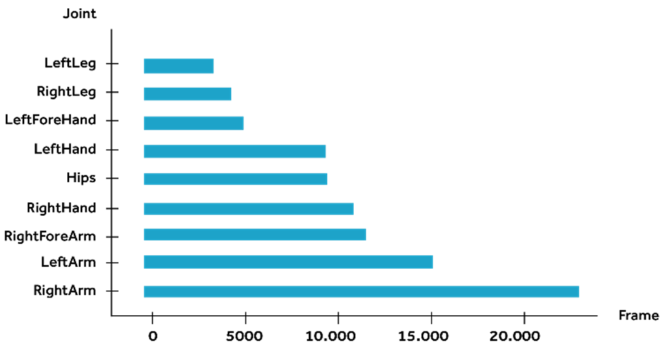


Fig. 7. Top 10 joints with the highest spatial complexity in the Remo dance. The x-axis indicated the frame count, illustrating the extent and variation of the 3D spatial movement exhibited by each joint throughout the dance sequence.

Although they support mobility, elements like the legs and pelvis exhibited lower spatial complexity, indicating a more limited spatial displacement. Hips are relatively difficult because the pelvic mobility maintains balance and smooth choreographic transitions. Research demonstrated that Remo dance's spatial structure and visual dynamics were dominated by the upper limbs, particularly the arms and hands, which emphasized expressive hand gestures and upper body articulation. Following the velocity and spatial complexity analysis, fuzzy rules were designed to emphasize the movements of both hands, notably the right hand, and both feet, focusing on the right foot, after the motion velocity and spatial complexity analysis. Table I presents the initial fuzzy rule set used in this system. This fuzzy rule set changed the camera angle and FOV based on fuzzy membership classifications across three terms - low, medium, and high - for both the motion velocity and spatial complexity. This broad architecture allowed the system to adjust the visual framing to movement intensity and dispersion. When motion was slow or static, the system selected an eye-level camera with a medium FOV for impartiality. When lower limb movements exhibited high velocity and complexity, a low-angle view and wide FOV were chosen to emphasize footwork dynamics in a larger spatial context. For strong hand motion intensity, a frog angle with a narrow FOV were dominated to enhance the upper limb gestures, independent of the foot movement. If feet dominated both parameters, the system employed a low angle with a wide FOV to capture the lower-body movements in a wider frame. The professional evaluations led to adjustments of the fuzzy rule base. The updated fuzzy rule set, optimized for the Remo dance's motion profile, is presented in Table II. The high angle and medium FOV provided balanced and complete views of fans and shawls. Figure 8 depicts the fuzzy input variable velocity and spatial complexity membership functions. The velocity membership function in Figure 8(a) comprised three parts:

TABLE I. FUZZY RULES FOR DETERMINING THE CAMERA ANGLE AND FOV

Hand		**Leg**		**Camera angle**	**FOV**
Velocity	**Complexity**	**Velocity**	**Complexity**		
Low	Low	Low	Low	Eye level	Medium
Low	Low	Medium	Medium	Eye level	Medium
Low	Low	High	High	Low angle	Wide
Medium	Medium	Low	Low	Eye level	Medium
Medium	Medium	Medium	Medium	Eye level	Medium
Medium	Medium	High	High	Low angle	Wide
High	High	Low	Low	Frog angle	Narrow
High	High	Medium	Medium	Frog angle	Narrow
High	High	High	High	Low angle	Wide

- Low: A decreasing linear function with full membership (μ = *1*) at a velocity of 0, tapering to at velocity of 2.
- Medium: A triangular function peaking (μ = *1*) at a velocity of 3.5, covering the moderate motion intensities from 2 to 10.
- High: A linear function from inactivity (0-5) to full membership at 10.

In Figure 8(b), the spatial complexity membership function was identical but scaled differently.

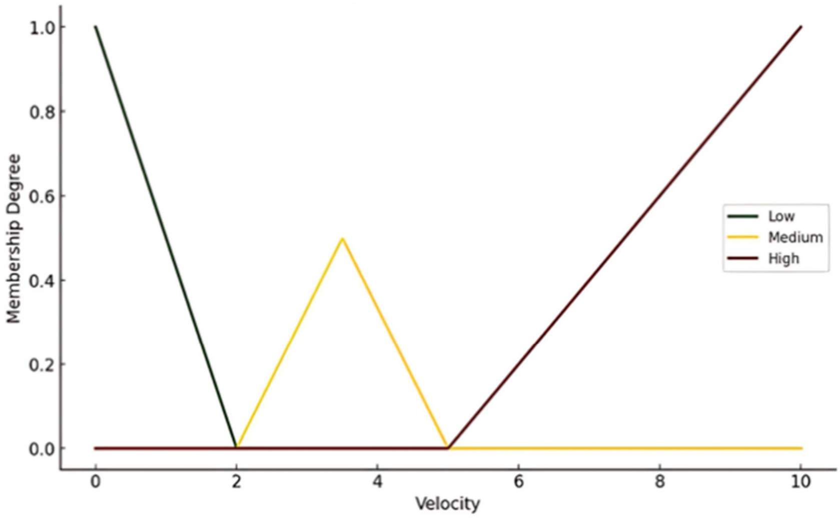
- Low: A decreasing linear function having full membership at 0 and zero at 1,500.
- Medium: A triangle centered at 2,300 (full membership), ranging from 1,500 to 6,000.
- High: The complexity increased linearly from 3000 to 6000.

Figure 9 presents the system's camera transition outputs in real time, demonstrating its capability to respond to performance dynamics. For example, based on the fuzzy inference rules and defuzzification process, one case resulted in a low camera angle of 67.5° and a medium FOV of 60.0°. The low perspective emphasized the footwork, while the middle FOV framed the image neutrally and contextually. For the Remo dance documentation, the camera setup mimicked the adaptive behavior.

TABLE II. FUZZY RULE EVALUATION OF CAMERA ANGLE AND FOV ADJUSTMENTS BASED ON MOTION CONDITION TRANSITIONS

Condition (Before)	Camera Angle (Before)	FOV (Before)	Condition (After)	Camera Angle (After)	FOV (After)
Low Velocity (Hand), Low Complexity (Hand), Low Velocity (Leg), Low Complexity (Leg)	Eye Level	Medium	High Velocity (Hand), High Complexity (Hand)	Frog Angle (90°)	Narrow (45°)
Low Velocity (Hand), Low Complexity (Hand), Medium Complexity (Leg), and High Complexity (Leg)	Eye Level	Medium	High Velocity (Leg), High Complexity (Leg)	Low Angle (30°)	Wide (105°)
Low Velocity (Hand), Low-Complexity (Hand), High Velocity (Leg), High Complexity (Leg)	Low Angle	Wide	Low Velocity and Complexity	Eye Level (0°)	Medium (75°)
Medium Velocity (Hand), Medium Complexity (Hand), Low Velocity (Leg), Low Complexity (Leg)	Eye Level	Medium	Medium Velocity, Medium Complexity	High Angle (60°)	Medium (75°)
Velocity (Hand), Medium Complexity (Hand), Medium Velocity (Leg), and Medium Complexity (Leg)	Eye Level	Medium	High Velocity and High Complexity (Hand and Leg)	High Angle (60°)	Wide (105°)
Medium Velocity (Hand), Medium Complexity (Hand), High Velocity (Leg), High Complexity (Leg)	Low Angle	Wide	-	-	-
High Velocity (Hand), High Complexity (Hand), Low Complexity (Leg), Low Complexity (Leg)	Frog Angle	Narrow	-	-	-
High Velocity (Hand), High Complexity (Hand), Medium Velocity (Leg), Medium Complexity (Leg)	Frog Angle	Narrow	-	-	-
High Velocity (Hand), High Complexity (Hand), High Velocity (Leg), High Complexity (Leg)	Low Angle	Wide	-	-	-

(a)



(b)

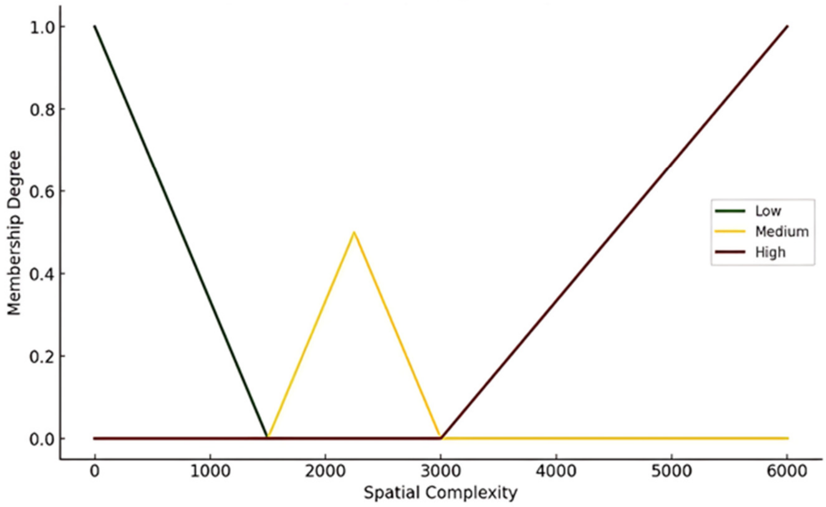


Fig. 8. Membership functions for fuzzy input parameters: (a) velocity membership functions categorized as low, medium, and high. (b) spatial complexity membership functions using the same linguistic variables. These membership functions guide the rule-based adaptive camera control system.

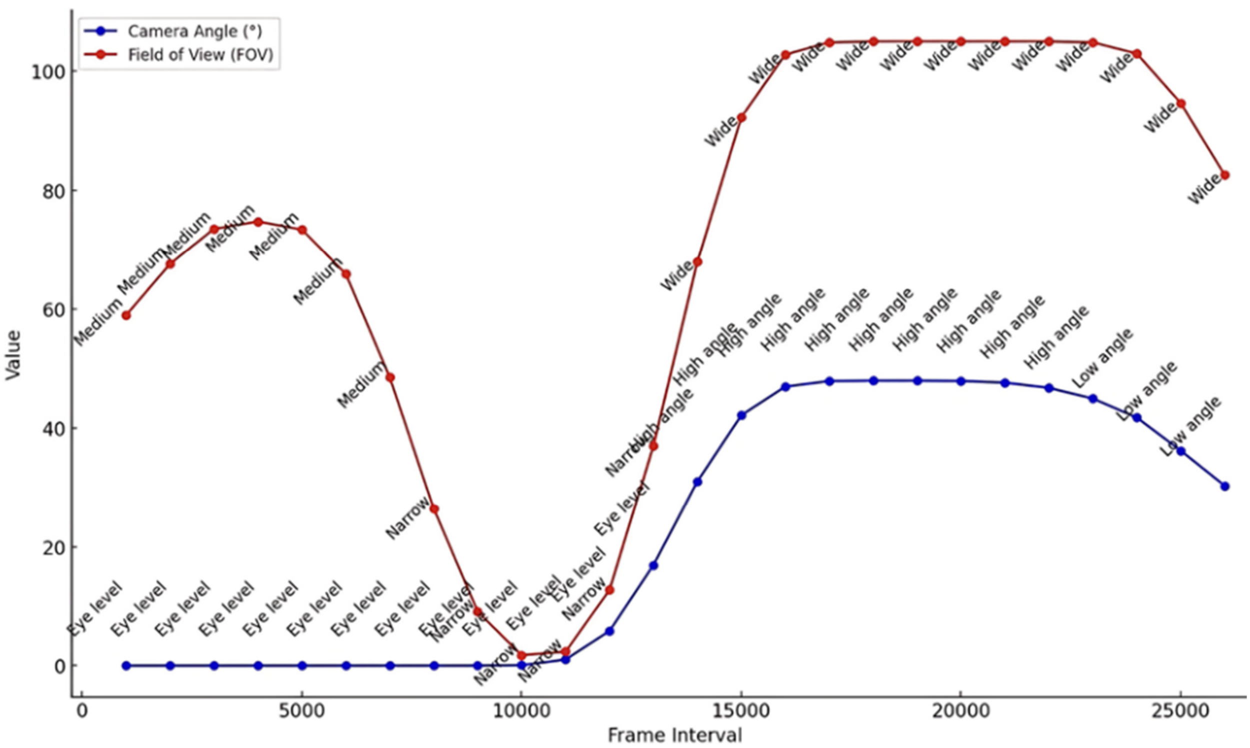


Fig. 9. Implementation results of fuzzy system controlling camera angle and FOV over time. The x-axis represents the frame intervals during the Remo dance sequence. The blue curve shows the adaptive changes in the camera angle, while the red curve indicates the variations in the FOV categories.

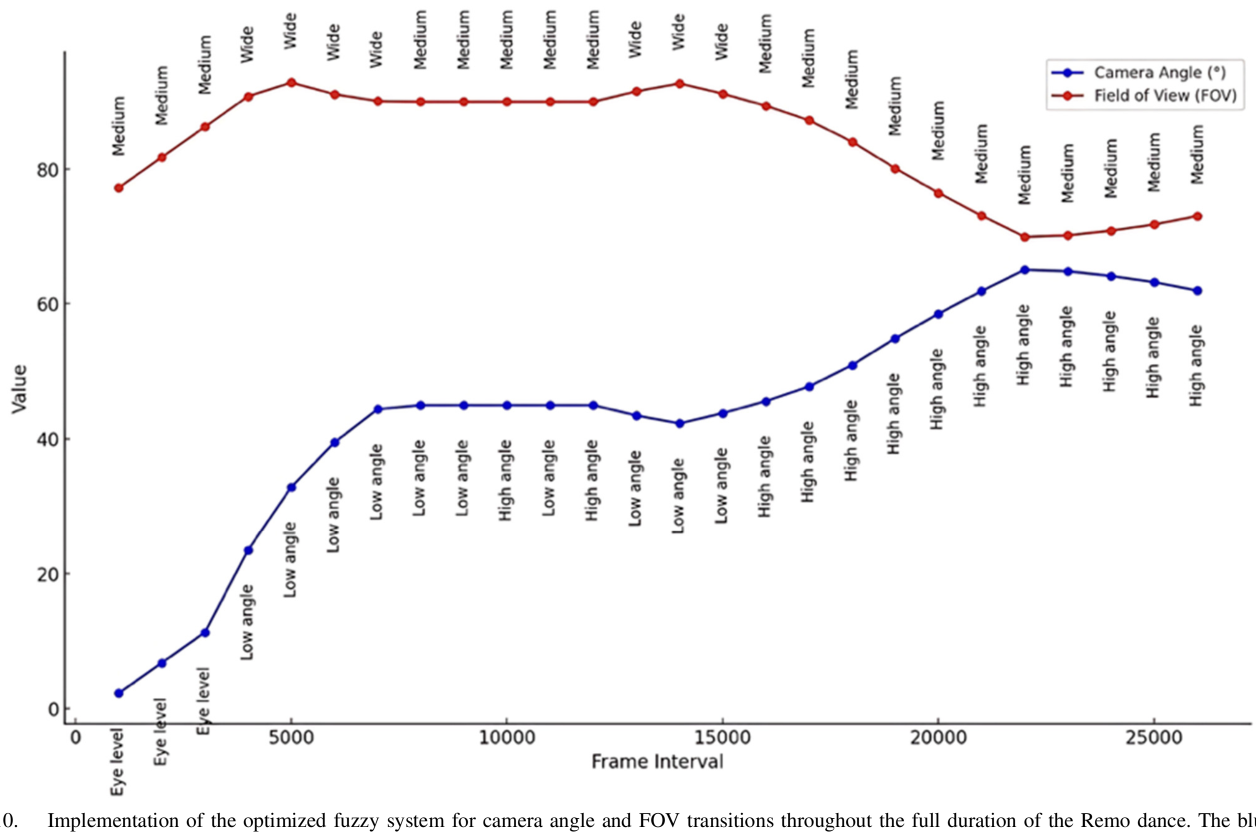


Fig. 10. Implementation of the optimized fuzzy system for camera angle and FOV transitions throughout the full duration of the Remo dance. The blue line represents the changes in the camera angle (in degrees), while the red line shows the corresponding FOV adjustments.

Figure 10 depicts the results of the optimized fuzzy logic system. The camera angle alterations are represented by blue lines and the FOV changes by red lines. The velocity and spatial complexity were monitored by multiple cameras. The frog angle and narrow FOV displayed aggressive hand movements, whereas the low angle and broad FOV demonstrated forceful footwork. The transitional or passive vision was balanced by the eye level and midfield FOV. The visual storytelling enhanced the dance documentation as a cultural asset and narrative.

Table III presents the MOS provided by experts in dance and cinematography, evaluating the system's performance across three key dimensions: cinematography quality, camera angle effectiveness, and cultural representation, both before and after system optimization. A strong expert scores for cinematography (8.1), angle effectiveness (7.7), and cultural portrayal (7.9) were achieved after the revised fuzzy logic system. The overall accuracy was 79%.

Table IV shows a comparison in the system performance between the adaptive fuzzy logic-based system and conventional manual video documentation. It was revealed that the system achieved a 25% reduction in the production time, increasing the overall efficiency. This trial proves that it works for historic documentation, digital preservation, and educational material.

Table V presents a detailed evaluation of the MOS across three experimental scenarios, including: the baseline rule configuration (5.1), the refined symbolic transition rule set (5.2), and the full system implementation (5.3). The average MOS increased from 77.3% to 79.5% between those rules. Table VI offers a comparative overview of the current fuzzy system, the conversional documentation method, and previous studies.

TABLE III. MOS FROM DANCE AND CINEMATOGRAPHY EXPERTS

System development by Fuzzy System			
Expert	**Cinematography Quality**	**Camera Angle Effectiveness**	**Cultural Representation**
Average	7.95	7.6	7.69
After optimized by system evaluation by experts and Fuzzy System			
Average	8.1	7.7	7.9

TABLE IV. SYSTEM PERFORMANCE COMPARISON: ADAPTIVE VERSUS CONVENTIONAL APPROACH

Evaluation Metric	**Adaptive System**	**Manual Video**
Process Time Reduction	25% faster	Baseline
Visual Adaptability	High	Medium
Dramatic Symbolic Emphasis	Present	Absent
Motion Dynamics Responsiveness	Real-time	Static
Overall Documentation Quality	Superior	Moderate

TABLE V. MOS EVOLUTION ACROSS EXPERIMENTAL SCENARIOS

Evaluation Criteria	**Baseline Rule (5.1)**	**Refined Rule (5.2)**	**Full Implementation (5.3)**
Cinematography Quality (MOS)	7.95	8.0	8.1
Camera Angle Effectiveness (MOS)	7.6	7.7	7.7
Cultural Representation (MOS)	7.69	7.9	7.9
Overall Accuracy (%)	77.3%	78.5%	79.0%

TABLE VI. COMPARISON OF DOCUMENTATION METHODS

Evaluation Criteria	**Fuzzy System**	**Conventional Video (Live Shot)**	**Previous Studies**
Process Time (Average)	25% faster	Baseline (100%)	
Cinematography Quality (MOS)	8.1/10	7.4/10	7.2 [16]
Camera Angle Effectiveness (MOS)	7.7/10	7.0/10	6.9 [2]
Cultural Representation (MOS)	7.9/10	7.2/10	Not evaluated
Visual Adaptability to Movement	High (Adaptive)	Medium (Manual Adjustment)	
Dramatic Emphasis (e.g., hand movement)	Frog angle and narrow FOV	General Eye-Level	
Coverage of Movement Dynamics	Time-Dependent Adjustments	Fixed Camera Settings	
Overall Accuracy (converted MOS)	79%	73%	
Expert Consensus	Strong Positive Feedback	Moderate Satisfaction	

IV. CONCLUSION

This study successfully introduced a fuzzy logic-based system for optimizing camera angles and Field of View (FOV) in the documentation of traditional dance performances. Motion parameters were utilized from BioVision Hierarchy (BVH) data, such as velocity and spatial complexity. The framework incorporated five camera perspectives (eye level, low angle, high angle, frog angle, bird's eye) and three classes of FOV (narrow, medium, wide), ensuring an accurate representation of expressive hand gestures and smooth transitional segments. The experimental evaluations confirmed its effectiveness, achieving a Mean Opinion Score (MOS) of 79%, with high marks in the cinematography quality (8.1/10), camera angle effectiveness (7.7/10), and cultural representation (7.9/10). Compared to conventional methods, the adaptive strategy reduced the production time by 25%, demonstrating its efficiency. Future work should focus on more efficient rule-tuning methods, extend the framework to other cultural performances, and investigate real-time implementation for immersive, adaptive visual storytelling.

ACKNOWLEDGMENT

Upie Guava, a pioneering director employing virtual production technologies in filmmaking, provided vital ideas and practical knowledge for this project. The authors thank the Faculty of Art and Design ITB, the Departments of Electrical Engineering, Computer Engineering, and Visual Communication Design ITS for their invaluable support in making this study a success.

REFERENCES

[1] D. Prasetyo, N. Ramadhani, M. Hariadi, and I. R. Mutiaz, "Lighting Dynamics for Emotional Perception: A Technology-Driven Virtual

Simulation Approach," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 22196–22202, Apr. 2025, https://doi.org/10.48084/etasr.10434.

[2] F. Multon, R. Kulpa, L. Hoyet, and T. Komura, "From Motion Capture to Real-Time Character Animation," in *First International Workshop*, Utrecht, The Netherlands, 2008, pp. 72–81, https://doi.org/10.1007/978-3-540-89220-5_8.

[3] L. Hu, "Dance Analysis and Visualization Method Based on Motion Capture Technology," *Computer Aided Design and Application*, vol. 21, pp. 117–130, 2024.

[4] K. Sun, "Research on Dance Motion Capture Technology for Visualization Requirements," *Scientific Programming*, vol. 2022, no. 1, 2022, Art. no. 2062791, https://doi.org/10.1155/2022/2062791.

[5] W. Zhen and L. Luan, "Physical World to Virtual Reality – Motion Capture Technology in Dance Creation," in *2020 International Symposium on Automation, Information and Computing (ISAIC 2020)*, Beijimg, China, Dec. 2020, https://doi.org/10.1088/1742-6596/1828/1/012097.

[6] I. Kico, N. Grammalidis, Y. Christidis, and F. Liarokapis, "Digitization and Visualization of Folk Dances in Cultural Heritage: A Review," *Inventions*, vol. 3, no. 4, Oct. 2018, Art. no. 72, https://doi.org/10.3390/inventions3040072.

[7] A. M. Baranowski and H. Hecht, "Effect of Camera Angle on Perception of Trust and Attractiveness," *Empirical Studies of the Arts*, vol. 36, no. 1, pp. 90–100, Jan. 2018, https://doi.org/10.1177/0276237417710762.

[8] M. Caramenti, P. Pretto, C. L. Lafortuna, J.-P. Bresciani, and A. Dubois, "Influence of the Size of the Field of View on Visual Perception While Running in a Treadmill-Mediated Virtual Environment," *Frontiers in Psychology*, vol. 10, Oct. 2019, https://doi.org/10.3389/fpsyg.2019.02344.

[9] B. Brown, *Cinematography: Theory and Practice: Image Making for Cinematographers and Directors*, 3rd ed. New York, NY, USA: Routledge, 2016.

[10] D. Stump and ASC, Digital Cinematography: Fundamentals, Tools, Techniques, and Workflows, 2nd ed. New York, NY, USA: Routledge, 2021.

[11] A. Orlandi, E. S. Cross, and G. Orgs, "Timing is everything: Dance aesthetics depend on the complexity of movement kinematics," *Cognition*, vol. 205, Dec. 2020, Art. no. 104446, https://doi.org/10.1016/j.cognition.2020.104446.

[12] X. J. Wu, Q. Li, and K. H. Heng, "Development of a vector-based fuzzy logic approach for motion planning," in *IEEE Conference on Cybernetics and Intelligent Systems, 2004.*, Singapore, Sep. 2004, https://doi.org/10.1109/ICCIS.2004.1460794.

[13] J. R. García-Martínez, E. E. Cruz-Miguel, R. V. Carrillo-Serrano, F. Mendoza-Mondragón, M. Toledano-Ayala, and J. Rodríguez-Reséndiz, "A PID-Type Fuzzy Logic Controller-Based Approach for Motion Control Applications," *Sensors*, vol. 20, no. 18, Jan. 2020, Art. no. 5323, https://doi.org/10.3390/s20185323.

[14] M. I. P. Azahar, A. Irawan, and R. M. Taufika, "Fuzzy Self-Adaptive PID for Pneumatic Piston Rod Motion Control," in *2019 IEEE 10th Control and System Graduate Research Colloquium (ICSGRC)*, Shah Alam, Malaysia, Aug. 2019, https://doi.org/10.1109/ICSGRC.2019.8837064.

[15] B. N. Lima *et al.*, "Artificial intelligence based on fuzzy logic for the analysis of human movement in healthy people: a systematic review," *Artificial Intelligence Review*, vol. 54, no. 2, pp. 1507–1523, Aug. 2021, https://doi.org/10.1007/s10462-020-09885-8.

[16] H. Junaedi, M. Hariadi, and I. K. E. Purnama, "Profiling Director's Style Based on Camera Positioning Using Fuzzy Logic," *Computers*, vol. 7, no. 4, Dec. 2018, Art. no. 61, https://doi.org/10.3390/computers7040061.

[17] E. Çakıt and W. Karwowski, "Soft computing applications in the field of human factors and ergonomics: A review of the past decade of research," *Applied Ergonomics*, vol. 114, Jan. 2024, Art. no. 104132, https://doi.org/10.1016/j.apergo.2023.104132.

[18] S.-J. Lee and H.-S. Chung, "Storing and Retrieving Motion Capture Data based on Motion Capture Markup Language and Fuzzy Search," *Journal of the Korean Institute of Intelligent Systems*, vol. 17, no. 2, pp. 270–275, 2007, https://doi.org/10.5391/JKIIS.2007.17.2.270.

[19] P. Szczuko, "Computer Animation System Based on Rough Sets and Fuzzy Logic," in *7th International Conference,Rough Sets and Current Trends in Computing*, Warsaw, Poland, 2010, https://doi.org/10.1007/978-3-642-13529-3_11.

[20] Y. S. Balcioğlu, A. Kiliç, and F. Pakdamar, "Modeling of laughing mimic caught with motion capture technology using fuzzy logic," *Social Sience Development Journal*, vol. 7, no. 34, pp. 296–311, Nov. 2022, https://doi.org/10.31567/ssd.786.