Fuzzy Logic-based Input Evaluation Method for Interactive 2D Animation Scene Design using Computer Vision

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Keywords: 2D animation, computer vision, fuzzy logic, variation detection

Received: August 29, 2024

Two-dimensional (2D) interactive animation engages the user to command and communicate with the design using touch and pointer functions. The user input delegates specific tasks for the design replicated on the screen through precise detection. This article introduces an Input Evaluation for Design-Specific Function (IE-DSF) method to improve the response precision of the 2D models. The user input through touch or devices is evaluated for sensitivity and design region for receiving commands. Based on the difference between input and response time and input region variations, the monotonous response of the design is computed. This computation is fuzzified for its unanimity throughout different input sequences. In this process, fuzzy logic-based validation is employed to determine minimum and maximum response time from the sequence of 2d design interaction. The maximum variation is used to improve the design sensitivity, and the minimum variation is used to increase the design functions on the screen. Therefore, the different recommendations correlate with providing frame-based 2D sequences with precise computer vision technology. The variation changes are reverted in the independent frames without modifying the entire design. This feature improves the consistency and evaluation of various interactive designs. The proposed IE-DSF method achieved a significant improvement of 9.38% in consistency, an 11.31% reduction in response time, and an enhanced interaction response of 8.8% across various inputs. With a considerable decrease in design modifications, reducing them by 11.1% helps optimize 2D animation design interactions.

Povzetek: Raziskava uvaja metodo IE-DSF, ki z uporabo računalniškega vida in mehke logike izboljša nteraktivne 2D animacije, zmanjša odzivni čas in optimizira spremembe oblikovanja.

1 Introduction

Interactive two-dimensional (2D) animation is a technology that allows users to interact and engage with the scene or design. It provides effective interactive services to the users to get real-time-based input [1]. The interactive 2D dimension delivers the target to the users and provides better conversion, minimizing network error. Interactive 2D animation scenes are also done using computer vision (CV) technology [2]. CV is a part of artificial intelligence (AI) that extract meaningful information from digital images and videos. The CV performs tasks based on information gathered from the images. The CV aims to identify the features and frequency of scenes that need to be created for the animation process [3]. The exact dimensions of the range of the scenes are calculated using CV, which minimizes the latency of the design process. The CV-based animation design provides users with immersive scenes and views [4]. CV provides detailed aspects of designing interactive 2D animation scenes in a movie or comic. Proper CV tools and techniques improve system design feasibility and efficiency [5].

Human input is referred to as the information which humans provide to artificial intelligence (AI) systems. Human input provides necessary information which instructs the application to perform tasks [6]. Human input analysis is used for the 2D design response process. The goal of input analysis is to analyze the relevant data for further designing processes [7]. To enhance the design process, scene transitions and visual clarity in animation and make animations more efficient, adaptive, and visually appealing, focus on different animation types [8]. The extracted data produce optimal information for the 2D design process. The vital features contain the necessary data to design or create 2D scenes for an application [9]. A convolutional neural network (CNN) based human input analysis model is also used for 2D design response. Both low- and high-level features and patterns are detected from the inputs, which minimizes the latency of the design process [10]. The CNN model recognizes the input's features and produces appropriate animation design datasets. The CNN model improves the performance and effectiveness range of the 2D designing process [11].

Fuzzy logic is an approach that analyzes the data based on functions. Fuzzy logic is commonly used in many fields to improve the overall performance range of the application [12]. Fuzzy logic is also used for the 2D design evaluation process. The main aim is to predict the systems' exact design sequence and features. A fuzzy logic-based evaluation approach is used for the 2D evaluation process [13]. Fuzzy logic is mainly used to identify the differences among parameters and functions. The detected features provide relevant information for 2D designing in a prompt response [14]. A fuzzy logic controller is used here to detect the necessary measures to perform tasks in the 2D design process. The fuzzy logic-based approach increases the accuracy of evaluation, improving the systems' efficiency level [15]. An adaptive fuzzy logic technique is also used for the design evaluation process. The fuzzy logic identifies the issues during design and produces an optimal solution to solve the problems. The fuzzy logic technique provides necessary designing patterns and factors for the 2D design that decrease the time consumption in the computation process [16, 17]. The contributions of the article are listed below:

- Designing a fuzzy-logic-based 2D animation sequence evaluation method for improving the interaction response and sensitivity.
- A fuzzy optimization method is provided for suppressing the variations across different sequences so that the frequent design modifications are restricted.
- A comparative study will be performed using different methods and metrics, including consistency, interaction sequence, promptness, design modifications, and response time, and the proposed method's consistency will be verified.

2 Related works

Table 1 summarizes the different methods discussed by the authors in the past.

Table 1: Summary of different methods

Author	Method	Key area	Technique used	Results	Precision (%)	Sensitivity(%)	Response Time (S)	Design Modification Rates (%)	Limitations
Choi et al. [18]	A unified visualization framework for interactive dendritic spine analysis.	It is used to categorize the features which are presented in the spine.	3D morphological features are used in the framework to produce relevant data for the analysis process.	Increases the accuracy in analysis and evaluation processes.	90	85	1	12	Struggles with real-time adjustments in high dimensional data analysis
Gay et al. [19]	A force-feedback tablet (F2T) architecture for 2D information.	The actual effects of feedback are identified by F2T.	F2T minimizes the energy consumption level in the computation process.	Recognize both spatial and temporal features of the datasets.	88	87	<1	10	Limited scalability for complex interactions
Velazc	A	AR is	Augmente	Provide	91	89	2	9	Faces

o-Garcia et al. [20]	computation framework for medical imaging.	mainly used to provide efficient data to the systems.	d reality (AR) is used in the framework to analyze the modules for optimization.	effective workflow in medical image processing systems.					latency issues in resource constrained system
Cárdenas-Sainz et al. [21]	A natural user interface (NUI) for interactive learning environments.	The exact positive attitude of the users is detected using NUI.	The technology acceptance model (TAM) is used in the system which predicts the interface based on functions.	Improves the performance range of the systems.	85	90	<1	15	Not robust in handling diverse real-time user behaviors
Zhang et al. [22]	A deep convolutional neural network (DCNN) method for interactive visual systems.	The high-resolution region and frequency are detected.	Provide high-quality services to the users.	Increases the efficiency range of the systems.	92	88	2-3	10	High computational demands
Chover et al. [23]	A 2D game engine for video game development systems.	It validates the exact quality of the video and gathers information via feedback.	The user's behavioral features are used in the engine.	Minimizes the complexity of the development process.	80	75	<1	20	Limited scalability
Xiang et al. [24]	A joint optimization framework for automatic design of robotics.	The main aim is to optimize the axes using hierarch	Provide optimal actions and functions to the systems.	Decreases the complexity of the optimization process.	87	85	3-5	12	Dependency on static design parameters

		ical actions.							
Wang et al. [25]	Gated neural network for character control	Calculate strategy variables	Uses deep learning to select mode adjustment posture for interaction characters	Increased interaction accuracy and efficiency in character control	90	92	<1	4	Limited flexibility for complex character movements
Zhou et al. [26]	H-GOMS model for VR evaluation	Identifies spatial and temporal interaction parameters	Quantitatively analyzes interactive behaviors and minimizes service latency	Improved VR system visualization in real-time	89	91	<1	2	Latency in large-scale multi-user VR environments
Wang and Zhou [27]	Fuzzy kano model for genetic algorithms	Handles customer demands through feedback	FKM model achieves high accuracy in decision-making	Improved efficiency and reduced energy use	95	93	2	3	Slow adaptation to changing customer preferences
Shi and Wang [28]	Optimization algorithm for virtual idol characters	Captures motion in interaction processes using ANN	Controls motion and virtual characters factors using ANN	Improves consistency and effectiveness in interactive systems	88	89	1-2	10	Struggles with real-time adjustments to new parameters
Yang [29]	Intelligent human action capture and recognition model	Human-Computer Interaction	Action structured Graph Convolutional Network, encoder-decoder architecture LSTM.	Average accuracy of 95.39%, and obtained F1-score 89.7%	95.3	Not analyzed	Reduced delay	Based on the VR animation setting	Time delay in current models, low recognition accuracy before implementation

Wang et al. [25] proposed a gated neural network framework for interactive character control (ICC-GNN). The proposed framework calculates the variables and modules presented in the strategy. The exact mode-adjustment posture for interaction characters selected using deep learning algorithms. The deep learning algorithm increases the accuracy of the interaction process. The proposed framework improves the efficiency range in the character control process.

Zhou et al. [26] introduced an H-GOMS model for virtual environment (VR) evaluation. Unique and temporal parameters are identified for interaction, minimizing the latency of providing services to users. The introduced H-GOMS model also analyzes the interactive behaviours using a quantitative analysis. The introduced model increases the real-time visualization range of VR systems.

Wang and Zhou [27] designed a fuzzy kano model (FKM) based method for an interactive genetic algorithm. The developed method is mainly used to evaluate the exact customer demands produced via feedback. The FKM model achieves high accuracy in the decision-making and preference detection process. Experimental results show that the designed method increases efficiency and reduces energy consumption in the computation process.

Shi and Wang [28] developed an optimization algorithm for virtual idol characters. An artificial neural network (ANN) is used here to capture the exact motion in the interaction process. The ANN controls the motion and parameters necessary for virtual characters. The developed algorithm predicts the optimization problems and solves the issues using solutions. The development increases the consistency and effectiveness range of the interactive systems.

Yang et al. [29] combined an encoder-decoder architecture with LSTM algorithms and an action-structured graph convolutional network. The Intelligent Human Action Recognition Model (IHAR) achieves an F1 score of 89.79% and a high accuracy of 95.39%. Its real-scene detecting performance is enhanced, and response delays are decreased. Time lags in action recognition are still an issue, and precise sensitivity measures are not yet known.

By fixing critical issues like inconsistent design sensitivity, high design modification rates, and restricted scalability, as discussed in Table 1, the proposed IE-DSF approach outperforms previous methods. It lessens the need for regular design tweaks and improves real-time performance, especially in high-dimensional data settings. IE-DSF is the way for more complicated and ever-changing systems because of its superior scalability and adaptability. Furthermore, it enhances decision-making using data-driven iterative procedures, guaranteeing enhanced sensitivity and precision. Where existing methods fail, this approach provides a strong replacement, especially when dealing with efficiency and complexity.

3 Problem definition

The proposed evaluation method focuses on suppressing the variations in animation sequences between different input intervals. The methods mentioned above/ techniques optimize the validations based on previous input responses. This retards the sensitivity-based analysis for different design functions and input commands. This proposed method identifies the optimal design pattern for handling such balanced issues using differential response and region-specific sensitivity output. Exceptionally, response promptness is considered for leveraging consistency across various inputs and reducing errors.

4.1 Proposed input evaluation for design-specific function method

The proposed DSF method is introduced to improve the consistency of the features in the input 2D animation design. The two-dimensional interactive animation between the user and the design is based on keyboard input, touch, and pointer functions. Access is evaluated for sensitivity Through touch or device, and the particular design region depends on better consistency with the available features. The evaluation of various interactive designs is prominent in this manuscript, and the variations will be thwarted through a fuzzy process. IE-DSF is a method that classifies the input response and design region with the receiving commands. The proposed method defines the user input delegates for the design relying on certain functions; this process is pursued by replicating the 2D design on the screen with precise region detection. The difference between input response time and input region variations is analyzed to evaluate the monotonous response of the design and achieve high response precision of the 2D models. The fuzzy process sequentially supports fewer time variations. This method ensures that fuzzy logic-based computation is performed to determine maximum and minimum response time from the sequence of 2D design interaction to improve response precision. The calculation of response time and design sensitivity is different for each region and is identified based on receiving commands from the users. In this scenario, the user commands and communicates with the two-dimensional design through enhanced pointer functions or touch. Therefore, this receiving command from the user is responsible for accurately identifying the minimum and maximum response time observed from the sequence of 2D design interaction adaptively with less variation and complexity. The minimum and maximum variations of time and sensitivity are modelled for the design functions (i.e.) the fuzzy logic-based validation is feasible to be employed for determining this variation within the same communication interval for its unanimity verification throughout different input sequences. Based on this variation, if the maximum variation is detected in any sequence, it indicates augmenting design sensitivity, whereas the minimum variation indicates increasing design functions on screen. This process recognizes design modification using the sequence of variation occurrence detection from the instance, where the two-dimensional design correctness is executed for communication interval. In Figure 1, the proposed method is illustrated.

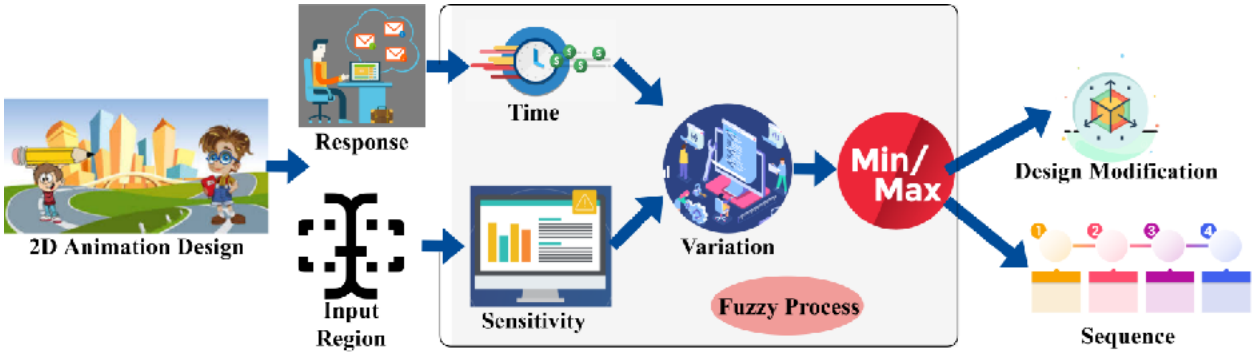

Figure 1: Overview of the proposed input evaluation for design-specific function method.

The process of IE-DSF for interactive 2D animation scene design-based functions acquires monotonous responses through commands received from the users. Certain design functions are processed to classify input response and region using time and sensitivity validation through a fuzzy process. The classification output detects the minimum or maximum variation through recommendation correlation from the sequence of 2D design interaction. The design-specific function analysis method improves the response precision when the design modification is initially recognized. The input 2D animation scene functioning $f(x,y)$ for the design is represented as in Equation (1-3).

$$f(x,y) = \frac{1}{C_i}\sum_{r^{cmd}=1}^{C_i} RT_I(r^{cmd}) - RG_I(r^{cmd}) \quad (1)$$

Where in Equation (1), the computation of $f(x,y)$ measures the performance of the 2D animation scene by calculating the average difference between input response time and input region variations for received commands over the communication interval, indicating how well the animation responds to user inputs.

$$RT_I(C_i) = \frac{1}{\sqrt{2\pi}}\frac{(4x+3y)^2}{C_i} \quad (2)$$

And,

$$RG_I(C_i) = \frac{-xy+2y^2-3x^2}{C_i} \quad (3)$$

Where the variables $RT_I(r^{cmd})$ and $RG_I(r^{cmd})$ means the input response time and input region variations observed from the given 2D animation scene design for the receiving commands r^{cmd} within the communication interval C_i. Equations 2 and 3 describe the system's behaviour continuously and smoothly by modelling the input data response time and regional variations using functions similar to Gaussian distributions. If x and y denote the minimum and maximum response time for time T for improving response precision, then $RT_I \in [0,\infty]$ and $RG_I \in [-\infty, 0]$.

4.2 Introduction to data

The proposed method is validated using a 2D animation sketch performing different actions. The action sequence includes running, walking, jumping, talking, reacting, etc. The selected actions, running, walking, and jumping, represent everyday human movements. A touch sensitivity of 30% has been chosen based on user testing to balance responsiveness and prevent accidental triggers, while the 5 ms response time meets industry standards for real-time interactivity. User testing confirmed that the response time below 10 ms felt seamless, making it an optimal choice. The animations have been rendered at 60 fps using the .bvh file format on a system. Data collection involved performing each action ten times by three actions for standardized animations. These additions will enhance the clarity and reproducibility of the proposed study.The interaction is designed as touch/ command line input to get a response. The design region is calibrated with 30 % touch sensitivity and a 5 ms command response. This information is extracted as $.bvh\,file$ with a maximum of 2605 count. The animation sequence is observed at 60fps and is classified under 23 classes. In this animation sequence, the skeleton structure is designed with 50 joints. A sample of the design is illustrated in Figure 2.

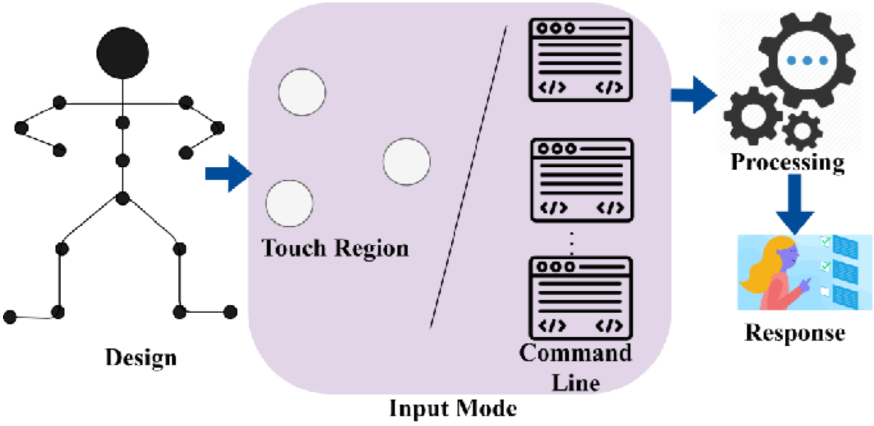

Figure 2: Sample illustration of the design functions of fuzzy logic controller configuration.

As represented in Figure 2, the input mode is calibrated based on interactive sensitivity and response time (promptness). Here, this method analyses the promptness and sensitivity variation for variations using a fuzzy process. The consecutive sequences (input) and their output determine the design modification. Based on the user input, the sensitivity and design region based on receiving commands are estimated as

$$\left.\begin{array}{c} RT_I(T) = \frac{1}{\sqrt{3\pi}} \int_{-\infty}^{\infty} x_{C_i}(T)\, dT \\ and \\ RG_I(T) = \frac{1}{\sqrt{3\pi}} \int_{-\infty}^{\infty} y_{C_i}(T)\, dT \end{array}\right\} \quad (4)$$

Based on Equation (4), the maximum response time is suppressed with the fuzzy process for computing its unanimity for the complete input sequence based on x and y values at different time intervals $(\text{C} \times T)$. These parameters $RT(T)$ and $RG(T)$ integrates fuzzy logic into the system, using F_x and F_y to account for uncertainty in user inputs. The term $(\text{C} \times T - 2^u)$ allows for non-linear scaling based on time and computed unanimity. Here C is the input sequence classification using fuzzy logic.

Fuzzy Rule Setting:

Rule 1: The fuzzy controller uses predefined rules to link user input characteristics like response time and sensitivity to design modifications that include

Rule 2: IF response time is >50ms, THEN increase touch sensitivity.

An expert understanding of animation characteristics and user interactions is the basis of these specifications.

Membership Functions:

Membership functions μ_L define how inputs relate to fuzzy sets and are calculated using triangular membership functions defined by parameters (a, b, c).

$\mu_L(x) = 1$ if $x \leq 20ms$, decreasing to 0 at $x \geq 30ms$

If the input region variation is <20%, maintain the current animation function. In the fuzzy rule adjustment, the parameters are optimized using data from user interactions, adjusting membership functions to reflect observed behaviours accurately, indicating that a fuzzy inference system processes the required design modifications through fuzzy rules.

Classification is performed to reduce the response time and sequential variation occurrence in $f(x, y)$. Design modification is due to the variation observed in a certain region while receiving a command in any T. This proposed method follows maximum consistency for the available features that are computed as

$$\left.\begin{array}{c} RT(T) = \frac{x_{C_i}(T) * \frac{u}{2} F_x}{(\text{C} \times T - 2^u)} \\ and, \\ RG(T) = y_{C_i}(T) * \frac{u}{2} F_y(\text{C} \times T - 2^u) \end{array}\right\} \quad (5)$$

Where,

$$\left.\begin{array}{c} F_x = DS(T) \frac{F_x(T)_{u-1}}{3} \\ and, \\ F_y = DF(T) \frac{F_y(T)_{u-1}}{3} \end{array}\right\} \quad (6)$$

In the above Equations (5) and (6), the variables F_x and F_y are the fuzzy processes for minimum and maximum variations. In this equation 5, F_x and F_y represent fuzzy processes for the minimum and maximum variations in input response time and region. They are significant for modelling uncertainty in user inputs. The relationship to design sensitivity $DS(T)$ reflects how sensitive the design is to changes in inputs influenced by F_x and F_y defined in Equation (6), higher variations indicate increased sensitivity. The variable design function $DF(T)$ describe the system's behavior based on current input conditions with F_x and F_y guiding how well the design adapts to varying inputs. The variable $DS(T)$ and $DF(T)$ represents the design sensitivity and function based on variation detection from the sequence of 2D design. Based on the frame-based sequence occurrence of the design relies on x or y, the design sensitivity/function is for augmenting the response precision of the 2D models. The variable u indicates that unanimity is computed based on the response of the given design validation for variation detection. Figure 3 presents the Output generation process for the design response.

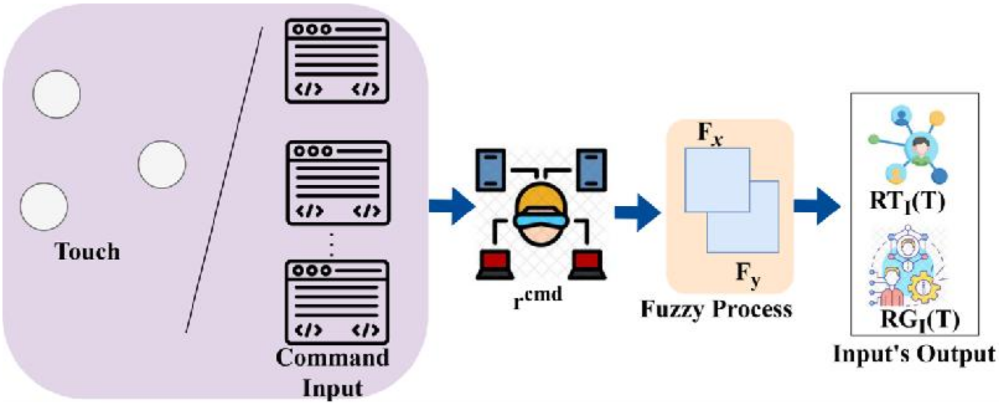

Figure 3: User interaction flowchart and design response.

The r^{cmd} is the actual input acquired from the user. This command executes the operation intended by the design. Based on the design's sensitivity and response (time), the fuzzy optimization is performed for which RT_I and $RG_I \, \forall \, T$ is identified. This process is congruent for F_x and F_y such that any input flew is identified for modification. The modification relies on sensitivity improvement/ variation minimization (Figure 3). Now, the input evaluation for design-specific function based on $RT(T)$ and $DS(T)$ is determined as in Equations (7) - (9). With this $F_x(T)_{u-1}$ variable scaled by the unanimity factor u in Equation (7) and normalized by the communication interval C_i to compute the function $f[(x,y), DF(T)]$. The term $[F_x - F_y]$ represents the difference between the minimum and maximum variations, highlighting how these fuzzy processes influence the overall input function for the design function $DF(T)$.

$$f[(x,y), DF(T)] = \frac{F_x(T)_{u-1}}{C_i}\left[F_x - F_y\right] \quad (7)$$

$$= \frac{2^u}{T}\left[\int_0^{\infty} \frac{F_x[(C\times T)-(DS(T)+DF(T))]}{T}\,dT - \int_{-\infty}^{0} \frac{F_y[(C\times T)-(DS(T)+DF(T))]}{T}\,dT\right] \quad (8)$$

Based on the above equations, the variation less $f[(x,y), DF(T)]$ design is observed after the fuzzy process. From this $f[(x,y), DF(T)]$ condition, two features, time and sensitivity, are extracted for further processing. The dynamic relationship discussed in Equation (8) between F_x and F_y across time intervals using integrals captures the cumulative effects of these fuzzy processes over time, considering both positive and negative time intervals. The factor $\frac{2^u}{T}$ serves to normalize the contributions of these fuzzy processes, ensuring that their influence on the overall function is balanced and responsive to variations in the design sensitivity $DS(T)$ and design function $DF(T)$. The dynamic relationship Equation (9) is used to compute the maximum variation (V_{max}) and minimum variation (V_{min}) for response time and design sensitivity, and hence,

$$\left.\begin{array}{c} V_{max} = \frac{1}{C\times T}\sum_{C_i=1}^{T}(x-y)\Delta^{-1}, \forall\, T \in u \\ and \\ V_{min} = -\sum_{i=y}^{x} DS_{max} \log DS_{max_{RT}} \end{array}\right\} \quad (9)$$

In Equation (9), the minimum and maximum variations are detected from the input 2D animation design Δ using touch and pointer functions. Equation 9 computes the system's maximum and minimum variations V_{max} assesses the range between minimum and maximum response times over time while V_{min} examines the link between design sensitivity and response time. This fuzzy process is performed for minimum and maximum variation detection along with the sequence of 2D design interaction in various instances. This classification helps to differentiate the maximum variation detected design from the minimum variation detected design. Considering a single 2D design (a skeleton structure) for 5 different action responses (emotions, walk, run, crouch, and jump) the $DS(T)$ and $DF(T)$ are analyzed in Figure 4.

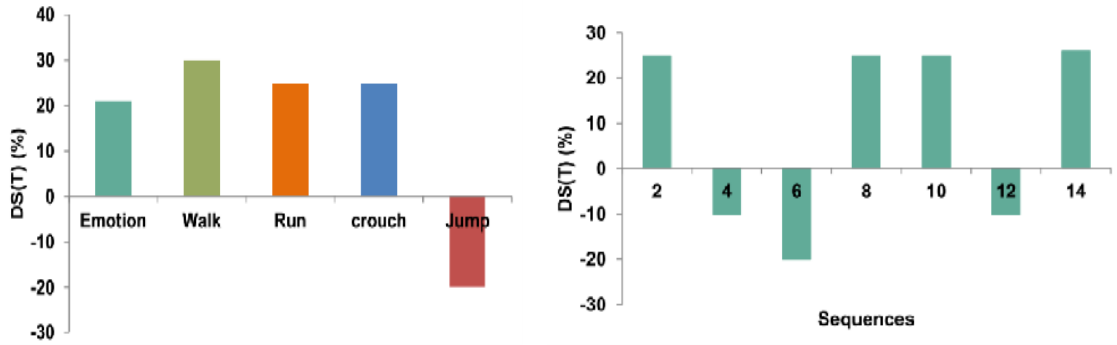

Figure 4 (a): Design function output precision.

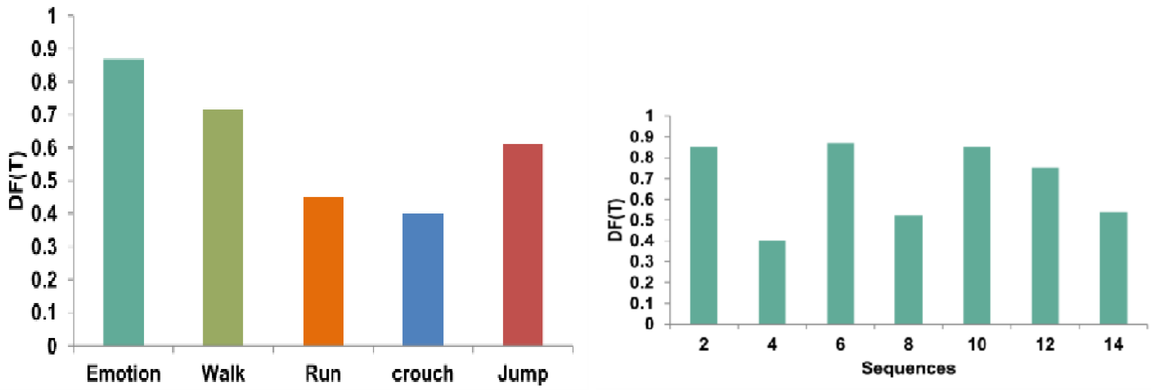

Figure 4(b): Sensitivity analysis of design functions.

The $DS(T)$ and $DP\ (T)$ are analyzed for the various activities and input sequences across RT_I and $RG_I(I)$. Based on the F_x and F_y The negative observations are mitigated such that the joint process of determining the minimum variation detection is identified. Such identification is addressed using C_i where the sensitivity and design-specific functions are retained for the same outputs. Therefore, the function is retrieved using r^{cmd} for different $f(x,y)$ improving the output precision (Figure 4(a) & 4(b)).

4.3 Variation detection

The touch or devices are responsible for receiving user commands and communicating with the design to improve consistency. The input response time and region variations are differentiated using a fuzzy process. In this different sequence input observation, the received commands (r^{cmd}) is computed as in Equation (10) & (11)

$$r^{cmd} = \frac{(V_{max} - V_{min})}{xy} + RT_{min} \quad (10)$$

And,

$$Vd = \frac{1}{\sqrt{2\pi}}\left(\frac{V_{min}}{V_{max}} - \frac{f(x)}{f(y)}\right) + 2(RT - DS) \quad (11)$$

Where the maximum and minimum variations are observed in different input sequences, the variable Vd denotes the precise variation detection with previous design information processed. The unanimity is estimated as the number of variation-detected sequences observed in various time intervals, for which the normalization is computed as:

$$\mathcal{N}orm(DF) = \frac{RT^2}{DS^2\left(\frac{V_{min}}{V_{max}} - f(x,y)\right)^2} \quad (12)$$

Equation (12) computes the normalization of 2D animation design interaction following the maximum and minimum response time identified based on input region variations. In this proposed method, the consistency for the sequence of 2D design is maintained until the maximum response time. Table 2 represents the list of symbols and its representation

Table 2: List of symbols and its representation

Symbol	Definition
$f(x, y)$	The input 2D animation scene functioning
$RT_I(r^{cmd})$	Input response time for receiving commands
$RG_I(r^{cmd})$	Input region variations for receiving commands
C_i	Communication interval
T	Time
x	Minimum response time
y	Maximum response time
$DS(T)$	Design sensitivity at time TTT
$DF(T)$	Design function at time TTT
F_x	Fuzzy process for minimum variations
F_y	Fuzzy process for maximum variations
u	Unanimity computed based on design validation
V_{max}	Maximum variation
V_{min}	Minimum variation
r^{cmd}	Received commands
Vd	Precise variation detection
D_m	Design modification
e_r	Error occurrence
$\alpha(\theta)$	First 2D design
$\beta(\theta)$	Response of the design

The variation detection before and after fuzzy normalization is illustrated in Figure 5.

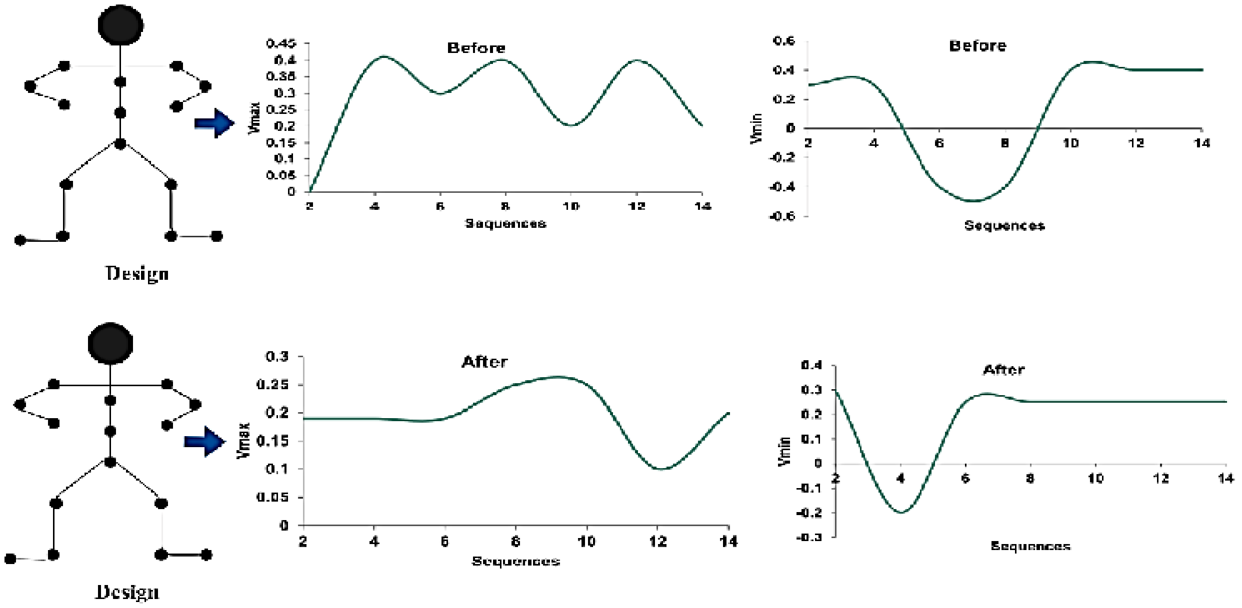

Figure 5: $\boldsymbol{min}$ and $\boldsymbol{max}$ variations in design modifications across input sequences.

Figure 5 validates the 2D design sequence for a small action change at different sequences. In this process, the min and max variations are considered for different input sequences. Here, the mouse pointer and the command line inputs jointly handle the sequence. Now u is the normalization process consideration for improving optimization. Therefore, the sequence that is similar to u is identified as preventing $V_{d_{max}}$. Here the e^r is identified in each fuzzification process such that normalization is maximum. The given two-dimensional design handled by the user depends on the response time mentioned in that design, which is maintained throughout the sequence. The above sequence of consistency is analyzed using fuzzy logic-based validation. In this scenario, the response time and design sensitivity are differentiated based on the minimum and maximum variation to improve the response precision. Besides, the different recommendations are heterogeneous in meeting the user commands and communicating with the design using pointer functions. Therefore, the various recommendations correlate with providing frame-based 2D sequences with precise computer vision technology. The output of the fuzzy process is to identify and segregate the minimum and maximum variation identified designs through response time and design sensitivity analysis.

Variation detection and recommendation correlation processes reduce the chance of design modification by causing errors. The identified errors are observed as a sequence of variation detection. The proposed design-specific function method focuses on such errors by matching minimum and maximum variation using a fuzzy process. In this method, the first 2D design is represented as $\alpha(\theta)$ such that the response of the design $\beta(\theta)$ is computed as:

$$\left.\begin{array}{c} \beta(\theta) = \alpha(\theta) - e^r * \left(\frac{V_{min}}{V_{max}} - f(x,y)\right) \\ such\ that \\ arg \min_{C_i} \sum e^r \ \forall \ RT \end{array}\right\} \quad (13)$$

In Equation (13), the variable e^r indicates the error occurrence, and the objective of minimizing variations for the sequence of 2D design interaction is determined. The input response time and regional variation are divided into two instances based on time and design sensitivity. The constraint $T = RT + DF$ achieves maximum consistency through the response time validation and region variation detection. Now, based on the sequence of $V_{max} \in T$ is to be validated on facing the first input design modification using sensitivity in a specific region. This is computed to identify design modification from the instance based on variation detection using a fuzzy process. The correlation of different recommendations using the available frame-based 2D sequences is provided through design functions. For this process, the frame-based two-dimensional sequence of $C_i \in DS$ with the use of computer vision technology for identifying design modification is expressed as:

$$D_m = \left(1 - \frac{RT}{Vd}\right) e^r * \left(\frac{V_{min}}{V_{max}} - f(x,y)\right) + \frac{1}{C_i}\int_0^\infty \frac{F_x[(C \times T) - (DS(T) + DF(T))]}{T} - \int_0^\infty \frac{F_y[(C \times T) - (DS(T) + DF(T))]}{T} \quad (14)$$

Equation (14) follows a sequence of 2D design interaction and variation detection for a precise design modification. The design modification is performed based on the $(V_{max_{D_m}})$ and $(V_{min_{D_m}})$ for maximum and minimum variation detected sequences at any instance is given as:

$$V_{max_{D_m}} = \frac{RT(T).RG(T)}{\sum_{i \in T}[C_i.u.\alpha(\theta)]_T} \quad (15)$$

And,

$$V_{min_{D_m}} = \frac{F_x(T).F_y(T)}{\sum_{i \in T}(C_{i\frac{u}{2}})_T\{[1-\beta(\theta)] \times RT(T)\}_T} \quad (16)$$

Equations (15) and (16) estimate the minimum and maximum variations in the 2D animation designs and are identified using RT and DS from the sequence of design interaction stored for future use. In this initial design modification process, the variation changes are reverted in the independent frames without modifying the entire design using a fuzzy process.

Pseudocode for IE-DSF Model

Input: Sequence of RT_I, RG_I, design

Output: design effectiveness

function IE-DSF (input_sequence, design):

initialize variables: RT_I , RG_I , DS , DF , V_{max} , V_{max}, e^r

initialize variables: $V_{max} = -\infty$, $V_{max} = \infty$

for each input in input_sequence ***do***

Step 1: Calculate input response time and input region variations

RT_I = Calculate RT_I (input)

RG_I= Calculate RG_I (input)

Step 2: Compute design sensitivity and design function

DS = Calculate $DS(RT_I, RG_I)$

DF = Calculate $DS(RT_I, RG_I)$

Step 3: Fuzzy process for variation detection

F_x = Fuzzy_Process (DS)

F_y = Fuzzy_Process (DF)

Step 4: Calculate variation

Vd = Calculate Variation (F_x, F_y)

Step 5: Detect maximum and minimum variations

V_{max}= max (V_{max},Vd)

V_{min}= max (V_{min},Vd)

Step 6: Calculate received commands

r^{cmd} = Calculate $r^{cmd}(V_{max}, V_{min})$

Step 7: Detect variation

Vd = Calculate $Vd(V_{min}, V_{max}, RT, DS)$

Step 8: Normalize design function

$\mathcal{N}orm(DF)$ = $\mathcal{N}orm(DF)$ $(RT, DS, V_{min}, V_{max})$

Step 9: Calculate design modification

D_m = Calculate $D_m(RT, Vd, V_{min}, V_{max}, F_x, F_y)$

Step 10: Calculate error

e^r = Calculate_Error (D_m)

Step 11: Update design

design = Update_Design (design, D_m, e^r)

Step 12: Calculate metrics

consistency = Calculate_Consistency($\mathcal{N}orm(DF)$)

interaction_response = Calculate_Interaction_Response(r^{cmd})

promptness = Calculate_Promptness(Vd)

design_modification = Calculate_Design_Modification(D_m)

response_time = Calculate_Response_Time(RT_I)

end for

return consistency, interaction_response, promptness, design_modification, response_time

end function

the IE-DSF pseudocode calculates performance metrics from an input sequence to assess design effectiveness,. Key variables including response time RT_I region variations RG_I design sensitivity DS, and design function are initialized. The model estimates response times, region variations, fuzzy logic variation detection, and design alterations depending on maximum and lowest variation values in each iteration. The model normalizes the design function and assesses consistency, interaction response, promptness, and reaction time. After computing these measures, the design is updated based on computed alterations and errors, producing effective performance indicators.

The consecutive processing of region variation detection helps to identify the error in 2D animation design between the instances. In the design modification, fuzzy logic-based computation is used to determine the correctness of the 2D animation design execution with minimum and maximum variation detection and computing sequence occurrence. As this fuzzy process relies on input response time and region variations, more reliable response precision is achievable through less response time and high sensitivity. The number of sequences may vary, although the previous 2D design interaction validation helps to classify the response and input region for both instances. In particular, this fuzzy process performs two types of validation, namely design sensitivity and design function. In the sequence design modification computation, V_{max} and V_{min} are independently identified to improve the evaluation of different interactive designs for communication intervals using touch or pointer functions. Instead, in the 2D design function, different input sequences of identified variation are used to improve the design sensitivity along with better validation. As per the process, the inputs for sequence design modification are based on time and sensitivity computation. The estimation of fuzzy logic is employed under minimum and maximum response time depending upon the occurrence of sequence to improve response precision and consistency. Based on the e^r and the $Norm\ (DF)$ performed the response for the $five$ designs on walking, running, crouching, jumping, and emotions are analyzed in Figure 6.

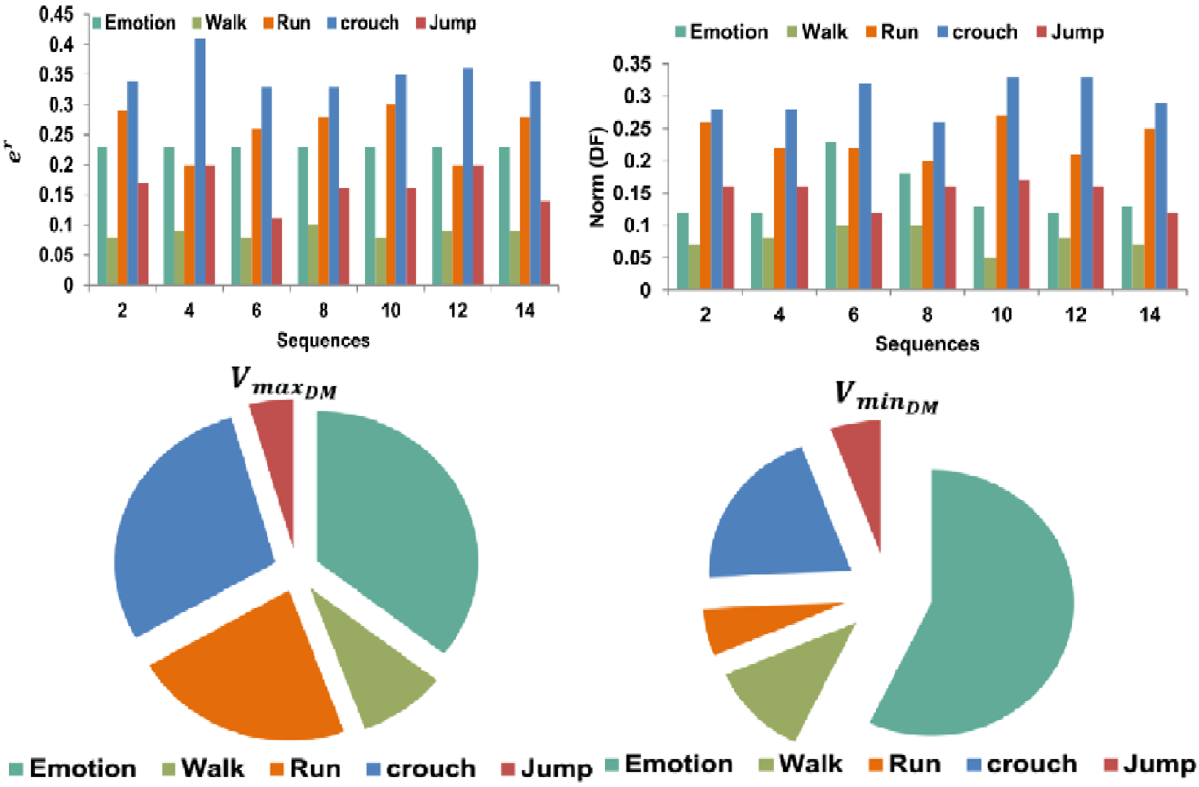

Figure 6: Error rate and design function analysis.

The fuzzy process is optimal for handling D_m such that the consecutive iterated process of $f(x,y)$ rectifies $V_{min_{D_M}}$. Based on the available solutions of D_m and the number of input sequences in the further process of $f[(x,y),DF(T)]$ is stabilized. In this process, stabilization is achieved using $\beta(\theta)$ and $\alpha(\theta)$ as the reference design. Therefore the e^r is reduced by inducing r^{cmd} for various inputs and responses. This is further fine-tuned using various sensitivity modifications to prevent variations (Figure 6).

4 Results and discussion

The metrics consistency, interaction response, promptness, design modification, and response time are validated in this section. In this comparative study, the number of inputs and designs varied from 2 to 30 and 1 to 12. The allied methods considered are ICC-GNN [25], IGA-FKM [27], and H-GOMS [26], along with the proposed IE-DSF method.

4.1 Consistency

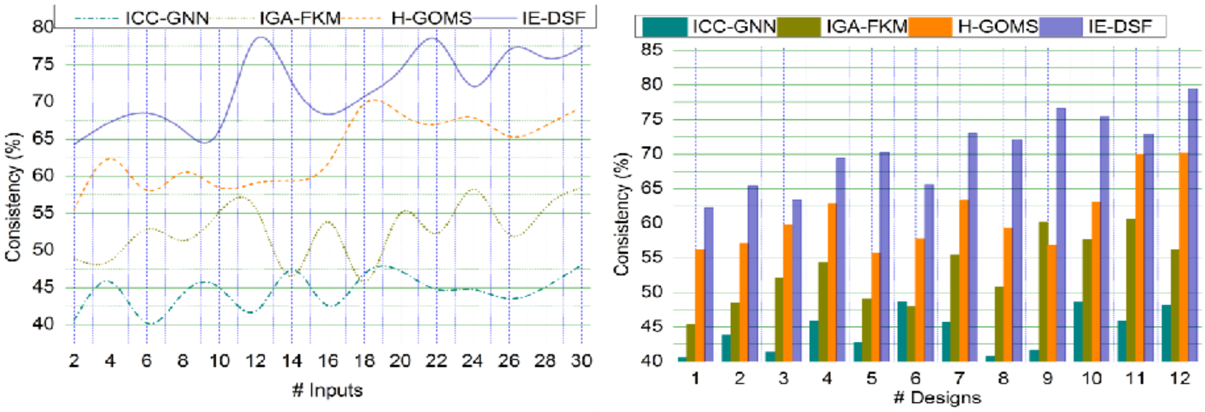

Figure 7: Consistency of user input responses.

In Figure 7, the user inputs through touch or pointer functions or devices to identify its sensitivity and design region to receive accurate commands for the design-specific function to improve consistency. The minimum and maximum response time is observed from the sequence of 2D design interaction for less design modification. Different recommendations are generated for increasing the design functions on-screen with the precise use of computer vision technology. Depending upon the response time and design sensitivity, validation using the fuzzy process segregates a specific region from the given design at different communication intervals. The fuzzy process correlated the various recommendations for providing frame-based 2D sequences to enhance consistency. From Equation (12), a normalized consistency $\mathcal{N}orm(DF)$ value for the design function DS^2 across various inputs and variations with a higher V_{max} value indicates better consistency in the design's response RT^2 to user inputs $f(x,y)$ compared to lower V_{min} design variable, contributing to a more reliable user experience based on the computation of consistency calculation using $DS^2\left(\frac{V_{min}}{V_{max}} - f(x,y)\right)^2$. This variation detection in 2D animation scenes is prominent in identifying sequence occurrences wherein the interaction response changes for all users due to high promptness and interaction response for the available design. This consistency factor is addressed using a fuzzy process, and high sensitivity is achieved for successive interaction responses, preventing design modification. Therefore, the consistency is high compared to the other factors.

4.2 Interaction response

This proposed method achieves a high interaction response for the user input with a particular function, and the variation detection is mitigated based on the unanimity of the different input sequences (Refer to Figure 8). The input region variations and input response time are computed to improve the design sensitivity by increasing the available features over different regions where the maximum variation is identified. Based on RT and DS measures, the difference between these features is analyzed, and the monotonous response of the design is achieved. The proposed method first classifies the input response time and region variation for possible region identification with improved response precision. The interaction response is estimated over the different areas with the previous data to reduce the response time and achieve high accuracy in variation detection. From Equation (10), the interaction response metric determines the system's reactivity to user input. The system's ability to quickly adjust to changes in user inputs is indicated by a higher r^{cmd} value, which improves the user experience with $\frac{(V_{max}-V_{min})}{xy}$ minimum and maximum design outputs with xy variables represents the input parameters affecting design response and minimum RT_{min} makes the proposed IE-DSF model better than other existing models. Therefore, fuzzy logic-based validation is pursued to improve the design function and the response time at different regions relying on user commands. Thus, this validation is to satisfy high interaction response using a fuzzy process. In this proposed method, the variation changes are reverted in the independent frames without modifying the entire design performed to identify the target region.

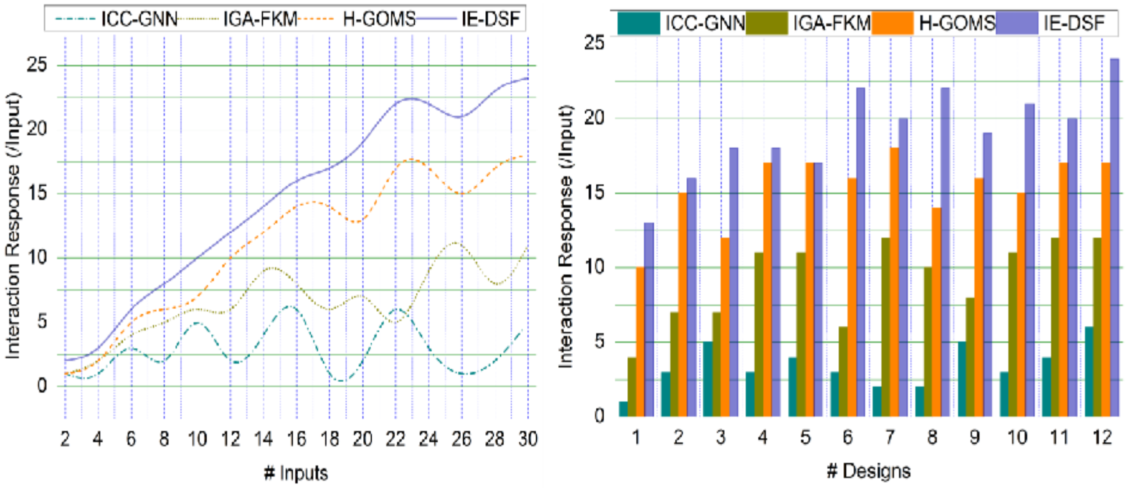

Figure 8: Interaction response comparisons.

4.3 Promptness

In this proposed method, the different input sequences for determining minimum and maximum response time from the sequence of two-dimensional design using fuzzy process rely on extracted features, making it easier to detect the sensitive region from the 2D animated design. The addressing of sensitive areas of appropriate and accurate 2D animation design makes it challenging to identify variations, and it is addressed using design sensitivity and design functions for response time to reduce the computation complexities at different instances. The errors are identified during sequential design interaction; this occurrence is determined through a fuzzy process. From Equation (11) the proposed IE-DSF calculates the variation detection based on the output values $\frac{1}{\sqrt{2\pi}}\left(\frac{V_{min}}{V_{max}} - \frac{f(x)}{f(y)}\right)$ and the response time $2(RT - DS)$ with associated design functions. A lower Vd indicates higher promptness, reflecting the system's ability to react quickly to user commands. From the overlapping features in the design, the distinguishable regions are correlated to identify the sensitive region without modifying the entire design in the input scene based on region segregation, preventing design modification. The continuous design functions on-screen are performed with fuzzy logic-based computation to improve response precision. Therefore, the design region identification relies on user commands to improve the design sensitivity sequence occurrence. In this proposed method, the computation is fuzzified for its unanimity using a fuzzy process to achieve high promptness, as illustrated in Figure 9.

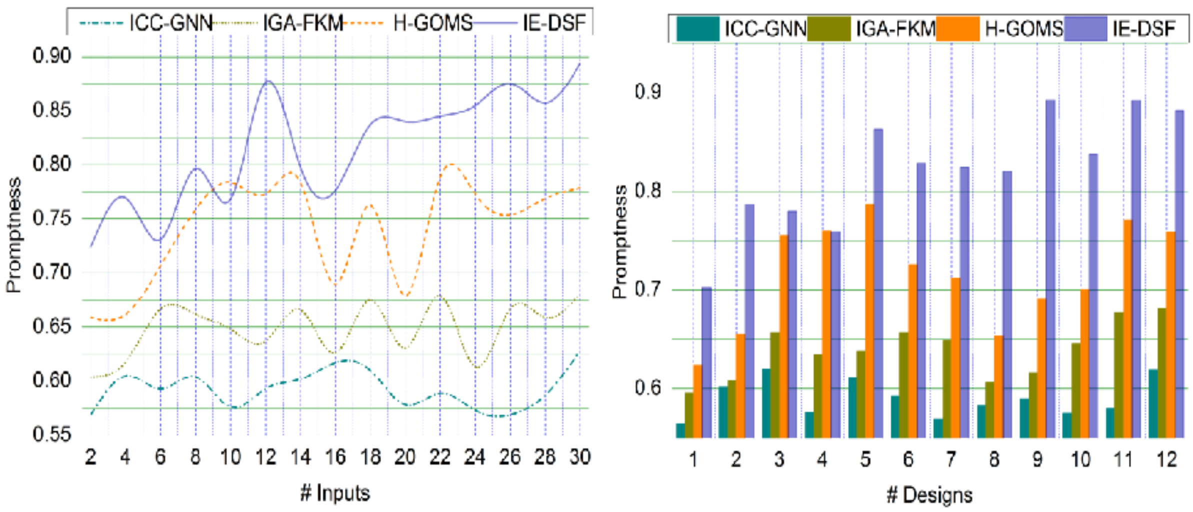

Figure 9: Promptness comparisons.

4.4 Design modification

This proposed IE-DSF method for minimum and maximum variation detection for the 2D design with precise, sensitive region selection achieves less design modification than the other factors in Figure 10. The distinguishable regions are combined to identify the input region variation using a fuzzy process, whereas the non-overlapping features can be distributed to provide frame-based 2D sequences. Reducing design modification at different response time intervals is computed to change variation detection from the sequence. The extracted features and available data are processed based on the receiving commands to improve the screen's design sensitivity and function. Equation (14) helps to assess the extent of design modification based on the response time $\frac{RT}{Vd}$, variation detection calculated earlier and error rate e^r associated with design modification. It improves the design's adaptability $\int_0^\infty \frac{F_x[(C\times T)-(DS(T)+DF(T))]}{T}$ and efficacy by helping to quantify the amount the design needs to change in reaction $\frac{1}{C_i}$ to user interactions. The design modification is mitigated through region selection and variation detection from the sequence of 2D design interaction. This makes it difficult to detect the variations in animation design in various instances. This method requires different recommendations to train the inputs in other regions. Thus, the proposed method estimates a fuzzy process for each design with less modification than a successful animation design.

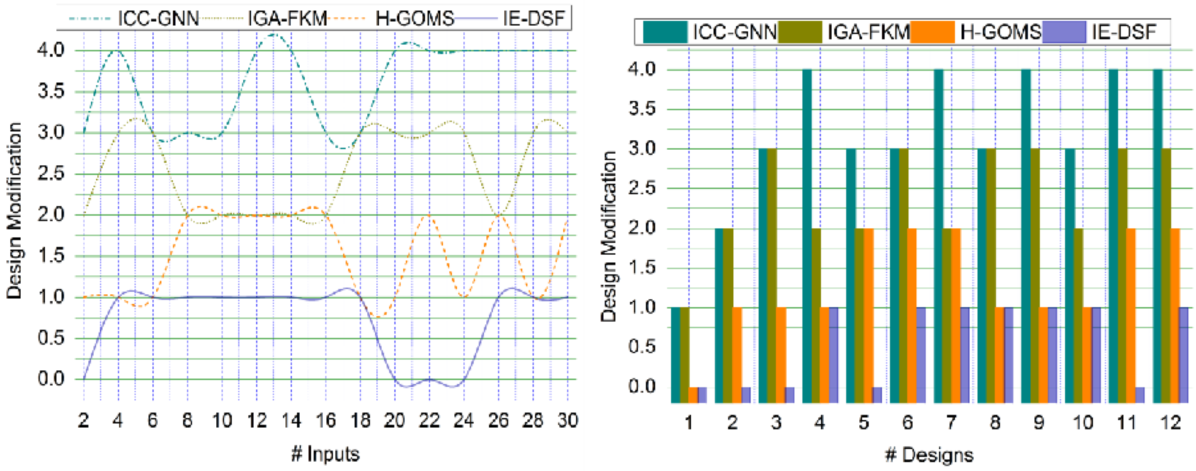

Figure 10: Design modification across input sequences and design comparisons.

4.5 Response time

In this proposed fuzzy logic-based evaluation for interactive 2D animation scene design, the minimum and maximum feature variations are detected to identify susceptible regions and achieve a high response time for the design (Refer to Figure 11). This process improves response precision with the fuzzy process and does not mitigate the design modifications and variations. It also identifies the region of interest using fuzzy logic from the sequence of 2D design interaction. Based on the variation changes are reverted, the maximum and minimum response time is segregated through the fuzzy process for accurate region selection based on $T = RT + DF$ and $V_{max} \in T$ for its maximum possible design modification is achieved. The input response time for a specific communication interval C_i providing insight into how quickly the system can respond to inputs with lower $RT_I(C_i)$ values indicate more efficient response times based on varying inputs and designs. In this manner, the maximum variation leads to improved design sensitivity, whereas the minimum variation leads to increased design functions on-screen with more precision. This method reduces response time and design modification to maximize the evaluation of various interaction designs. This design modification identified sequences are terminated, and the following sequence is processed using a fuzzy process. Hence, less response time is achieved using sensitive region identification for the design. The improvements from the comparative analysis summary are presented using Tables 3 and 4.

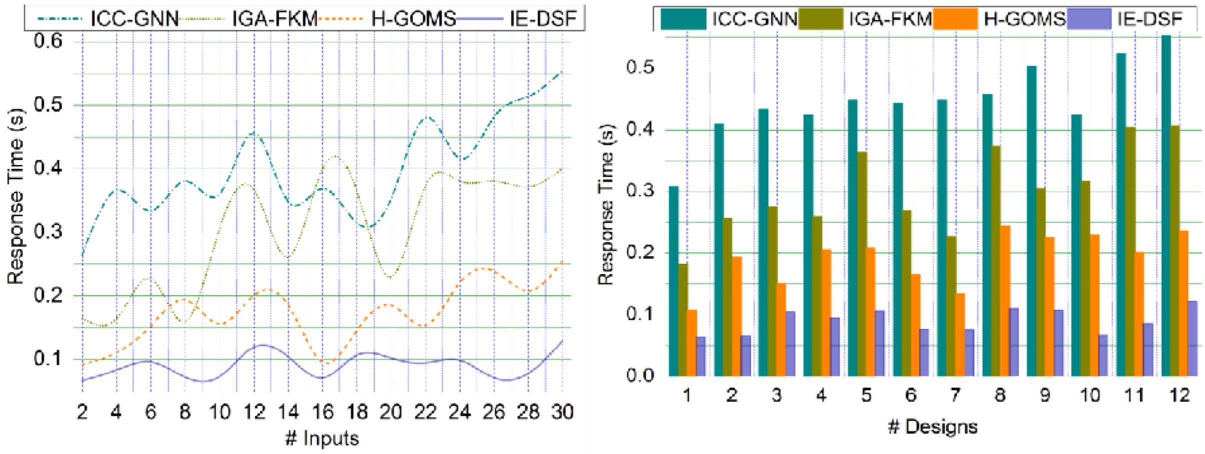

Figure 11: Response time comparisons.

Table 3: Comparative analysis improvements (# inputs)

Metrics	ICC-GNN	IGA-FKM	H-GOMS	IE-DSF	Improvements
Consistency (%)	48.06	58.41	69.29	77.35	9.38% High
Interaction Response (/Input)	5	11	18	24	8.8% High
Promptness	0.628	0.681	0.779	0.8935	9.88% High
Design Modification	4	3	2	1	11.1% Less
Response Time (s)	0.555	0.401	0.256	0.1299	11.31% Less

Table 4: Comparative analysis improvements (# designs)

Metrics	ICC-GNN	IGA-FKM	H-GOMS	IE-DSF	Improvements
Consistency (%)	48.14	56.21	70.22	79.48	10.65% High
Interaction Response (/Input)	6	12	17	24	8.56% High
Promptness	0.619	0.681	0.759	0.8818	9.77% High
Design Modification	4	3	2	1	11.1% Less
Response Time (s)	0.553	0.407	0.236	0.1214	11.58% Less

Compared to H-GOMS, the top-performing SOTA approach, which recorded 0.236 seconds, the IE-DSF method achieves a response time of 0.1299s on average, an improved and considerable reduction compared to others. IE-fuzzy DSF's logic-based architecture significantly contributes to this enhancement, which allows for real-time, dynamic modifications depending on user input patterns. Compared to SOTA systems that use fixed-parameter approaches, IE-DSF is superior because it uses fuzzy rules and membership functions to improve the system's responsiveness to different interaction settings and decrease input lag.

IE-DSF overcomes an existing model like ICC-GNN and IGA-FKM in interaction consistency, scoring 79.48% versus 70.22% and 56.21%, respectively. The adaptive fuzzy logic approach keeps the design stable and coherent across user inputs, improving consistency. The fuzzy controller in IE-DSF maintains interaction flow by modifying the layout depending on real-time input fluctuations, reducing the unpredictability of design behaviours. This adaptability lets the approach handle nuanced user input changes, making it more interesting.

Fuzzy logic improves responsiveness and distinguishes the IE-DSF method from standard approaches, highlighting its novelty and usefulness in increasing user interaction quality.

The IE-DSF approach also significantly improves sensitivity using system responses to user input. It can be fine-tuned using fuzzy logic, resulting in more accurate and context-appropriate design improvements. On the other hand, SOTA approaches like ICC-GNN and IGA-FKM do not possess this adaptive sensitivity. Therefore, they might not adequately consider subtle changes in the input, resulting in an over- or under-compensation of the design response. Improved user engagement and their associated satisfaction during the interaction are achieved by the IE-DSF method's ability to interpret slight differences in real-time and adjust the design accordingly, using fuzzy membership functions.

4.6 Limitation

While the suggested metrics can provide helpful information, they have some limitations, such as the fact that they may not accurately capture user interactions and that external factors like system load and environment can impact the results. The data sample size representation, and user contexts all introduce uncertainty and can mask accurate performance levels. In the future, research should focus on improving these measurements so they can be used more effectively in real-world situations and overcome these constraints.

5 Conclusion

This article proposes the input evaluation for the design-specific function method for validating the 2D animation design over varying sequences. The proposed method accounts for the response and input region for extracting the promptness and sensitivity measures. The variation for min-max observations throughout the animation function is validated in this process. The validations are performed using fuzzy optimization by considering the unanimity feature. Based on the unanimity feature, the sequences for different inputs are analyzed to achieve the optimal response in promptness at any interval. The fuzzification process is performed for response time-dependent variations such that the interaction is less complex for analysis. This prefers a design modification such that the functions are less considered for unanimous frames. Therefore, the structural and animation design modifications are revised for fewer levels to improve consistency by up to 9.38% for the different inputs.

Data availability statement

All data generated or analyzed during this study are included in this article.

Conflict of interest

The authors declare that they have no competing interests.

Funding statement

There is no funding in this article.

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