Animation Tools for Expressive Movement Design of Collaborative Robots With a Focus on Precision and Safety

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Abstract

Collaborative robots (cobots) constitute a class of robotic systems designed for safe, co-located operation with human users. Achieving effective and intuitive human-robot interaction (HRI) requires that cobots generate motion cues that are legible and semantically interpretable to non-expert operators. While engineering efforts traditionally emphasize control algorithms, motion constraints, and safety compliance, animation practitioners possess expertise in crafting expressive, human-readable movement that can inform more intuitive cobot behaviour design. However, most existing robot-animation workflows mathematically alter the animator-created motion to make it safely deployable onto physical robotic platforms, limiting the expressivity of the original motion design. To address this limitation, we developed a set of animation tools that enable an animator to directly design safely deployable expressive robot movements, grounded in two formal frameworks: Laban Movement Analysis (LMA) and Valence-Arousal-Dominance (VAD) model. These frameworks enable systematic mapping between movement qualities and perceived emotional content, providing a formal basis for expressive motion generation. The developed animator-centric tools can influence different aspects of the two frameworks and therefore facilitate animators in generating expressive motions for robotics systems. Each tool was evaluated using a tool-specific user study. Empirical results demonstrate that the tools helped decrease the number of adjustment iterations and improved the accuracy and consistency with which animators can design kinematically constrained cobot movements.

Keywords: human-robot interaction, animation tools, Laban Movement Analysis, valence-arousal-dominance model

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Introduction

As collaborative robots (cobots) become increasingly integrated into human work environments, ensuring their capacity to communicate efficiently and intuitively with human partners has become a central requirement. Effective HRI depends on transparent communication and an accurate user understanding of the robot's "mental model," defined as the human operator's awareness of a robot's capabilities, goals, and operational constraints (Tabrez et al., 2020). Although verbal communication is commonly used for explicit information exchange, everyday human interaction relies heavily on nonverbal cues (Burgoon et al., 2011). Incorporating analogous nonverbal communication mechanisms into robotic systems has been shown to improve joint task performance and increase users' willingness to collaborate with cobots (Breazeal et al., 2005).

Non-verbal communication by cobots can be achieved through hardware augmentation or expressive movement design. Hardware-based approaches augment robots with supplemental signals such as visual indicators: directional arrows, navigational markers (Szafir et al., 2015), blinkers, and beacons (Walker et al., 2018), or haptic feedback channels (Grushko et al., 2021) to enhance intention readability. In contrast, movement-focused design seeks to embed expressive motion directly into the cobot's kinematic behaviour. Early work in this space drew heavily on human behavioural analogues, leveraging the interpretability of human actions to inform robot expressivity (Lichtenthäler & Kirsch, 2013). Examples include artificial facial expressions (Banh et al., 2015), socially expressive trajectories derived from actor motion data, and gaze-based communicative cues (Hirano et al., 2017; Kompatsiari et al., 2019; Saldien et al., 2014).

Although human-behaviour imitation has demonstrated efficacy in improving HRI, its practical deployment is constrained by morphology-dependent motion capture data, which prevents generalization to simple or low degree-of-freedom (DoF) robots. These limitations have motivated the development of alternative paradigms, particularly expert-designed motion strategies (Fiore et al., 2013). Herein, trajectories are manually crafted using established movement and affective frameworks such as Laban Movement Analysis (LMA), Valence-Arousal-Dominance (VAD) model, Disney animation principles (Thomas & Johnston, 1995), etc. to preserve human-like expressivity in simple or low DoF robots.

Despite these advances, a significant implementation gap persists. While artists are frequently involved in the conceptualization and visualization of expressive trajectories, the final robot-executable motions often diverge substantially from the original designs due to hardware, kinematic, and environmental constraints (Ribeiro & Paiva, 2012). This issue stems from multiple factors, beginning with animation softwares such as Maya or Blender, which were originally developed for stylized and exaggerated animation, making it challenging to create expressive trajectories that follow strict robotic safety constraints (Ribeiro & Paiva, 2014). Although engineering softwares such as MATLAB can be introduced into the animation pipeline, this bifurcation between the creative and technical workflows disrupts continuity and hinders the animator's ability to iterate intuitively.

To address this challenge, our objective is to integrate technically grounded yet artist-centric tools into existing 3D animation environments, enabling animators to generate expressive, robot-compliant trajectories within familiar workflows. This paper presents the design, implementation, and evaluation of three animation tools developed for a low-DoF single-arm cobot in Blender. The primary contributions are:

- Conceptualization and initial investigation of animation-informed strategies for enhancing functional expressivity in cobots.
- Development of LMA and VAD informed animation tools to design quantifiable expressivity in low DoF single-arm cobots.

Background

The conceptual foundations of expressive motion were first established in the field of character animation, shaping early investigations of robot expressivity(Ribeiro & Paiva, 2014). Foundational work by Bates (1994) and Reilly (1996) drew heavily from traditional animation techniques, particularly those in The Illusion of Life (Thomas & Johnston, 1995). During the rise of 3D animation, Lasseter (1987) argued that classical principles remained broadly applicable across emerging media (pp. 263–264). Extending this view to robotics, van Breemen (2004) noted that user-interface robots face challenges similar to early animated characters, particularly the absence of an "illusion of life" and therefore advocated applying the 12 Principles of Animation in robotic systems, leading to the development of the expressive iCat platform (p. 2).

Subsequent research examined how animator-informed principles enhance social and communicative robot behaviours, with emphasis on gestural behaviour, character embodiment, and expressivity-driven interaction design (Beck et al., 2012; Thiebaux et al., 2008). More recent work reframed expressivity as a mechanism for functional communication in both humanoid and non-humanoid robots. This shift enabled practical integrations of animation and affective principles: for instance, Takayama et al. (2011) showed that the animation principle of Anticipation improves action legibility in PR2, while Terzioğlu et al.(2020) and Schulz et al. (2019) demonstrated that principles of Arcs, Appeal, and Slow In/Slow Out increase user comfort, predictability, and trust.

These developments naturally foreground the question of how animators might be directly integrated into robotic motion design workflows. Ribeiro et al. (2013) advanced this idea by examining how pre-existing character animations could be adapted for robotic platforms, arguing that robotic animation practice should leverage established character animation methodologies. They highlighted tools such as Unreal Engine (Epic Games, n.d.) and Houdini (SideFX, n.d.) as examples of systems that facilitate collaborative creative-technical pipelines. In parallel work, they introduced Nutty Tracks (Ribeiro et al., 2013), an animation engine built on 3D Max that integrates pre-designed animation pipelines with procedural correction algorithms to automatically enforce kinematic constraints including limits on velocity, acceleration, and jerk. Similarly, Starke et al. (2018) developed inverse kinematics (IK) systems enabling animators to construct robot trajectories via familiar IK rigs while automatically resolving complex robotic kinematic limitations.

Although these approaches represent meaningful progress in aligning artistic workflows with robotic constraints, most lack empirical validation regarding their impact on animator performance, workflow efficiency, motion fidelity, and the overall user experience for both creative and technical stakeholders. Consequently, a critical gap persists in understanding whether such tools substantially improve cross-disciplinary collaboration or expressive motion design outcomes.

To address this gap, we developed a set of animator-centric tools grounded in two structured frameworks: LMA and the VAD affective model. These frameworks enable systematic mapping between movement qualities and perceived emotional content, providing a formal basis for expressive motion generation. The developed animator-centric tools can influence different aspects of the two frameworks and therefore facilitate animators in generating expressive motions for robotics systems.

Related Works

This section presents the relevant literature on LMA and VAD model that together offer a systematic approach towards generation and perception of expressive robot motion.

Laban Movement Analysis (LMA)

LMA is a comprehensive theoretical framework for describing, interpreting, and structurally annotating human movement. LMA classifies movement into four major components: Body, Space, Effort, and Shape. The Body domain specifies which anatomical components are engaged and how their coordination patterns unfold. Space characterizes the spatial organization of movement, including directional vectors, trajectories, and geometric path structures. The Effort and Shape domains represent the qualitative and expressive dimensions of motion. Effort captures the internal motivational or intentional states driving movement, whereas Shape describes how the body's form evolves relative to spatial, functional, or emotional goals (Robin, 2011).

Within expressive robotics, the Effort component has been the most widely operationalized component (Raghu et al., 2025). Effort comprises four subdimensions: Space, Weight, Time, and Flow. Effort-Space describes attentional orientation toward a target, varying between Direct and Indirect pathways. Effort-Weight encodes perceived force or energy, ranging from Strong to Light. Effort-Time characterizes temporal modulation, from Sudden to Sustained pacing while Effort-Flow specifies the degree of movement continuity or restriction, differentiating Bound from Free motion profiles.

The Shape domain constitutes the second-most critical dimension relevant to robot expressivity. Shape is subdivided into Basic Shape Forms, Modes of Shape Change, Shape Qualities, and Shape Flow Support. Basic Shape Forms refer to global static configurations: Ball-like, Wall-like, Pin-like, Screw-like, or Pyramid-like geometries (Robin, 2011). Modes of Shape Change describe how the body reorganizes in relation to environmental affordances, categorized into Shape Flow, Directional, and Carving modes. Shape Qualities represent dynamic transformations toward or away from spatial targets, including Rising, Sinking, Spreading, Enclosing, Advancing, and Retreating. Shape Flow Support denotes torso-driven adjustments that facilitate or reinforce distal movement.

Bartenieff and Davis (1965) described the combined Effort-Shape framework as a complete system for studying behavioural and expressive movements, noting that emotional qualities and their intensities are systematically reflected in Effort, while Shape conveys spatial intention and morphological adaptation. Consequently, integrating both domains enables the parametric modulation of robot trajectories to encode affective and communicative subtleties.

Empirical studies substantiate this integration. Samadani et al. (2013) demonstrated that both Effort and Shape features can be quantitatively extracted from human arm kinematics and strongly correlate with expert LMA annotations, establishing measurable descriptors for computational modelling. Additional work in (Bacula & LaViers, 2020; Cheng, 2017; Masuda

& Kato, 2010) successfully deployed LMA-based Effort and Shape constructs on humanoid robotic platforms, validating their translational applicability. Extending this line of inquiry, Raghu et al. (2025) showed that a holonomic 7-DoF manipulator, kinematically comparable to the Kinova cobot used in this study(Kinova Robotics, 2020), can maintain stable Basic Shape Forms during motion execution, underscoring Shape's applicability in low-DoF motion design tools.

Informed by these findings, this work develops animation tools that can be used to control both Effort and Shape constructs to generate functionally expressive robot motion.

Valence-Arousal-Dominance (VAD) Model

VAD model is employed for quantitative representation, examination, and comparison of affective trajectories (Verma & Tiwary, 2016). The VAD model conceptualizes affective experience as a point within a three-dimensional, continuous, and orthogonal emotional space comprising: Valence, denoting the positivity or negativity of an emotional experience, ranging from pleasant to unpleasant; Arousal, reflecting the intensity of the emotional activation, ranging from passive/calm to active/excited; and Dominance, describing the perceived degree of control or agency, ranging from submissive to commanding.

The VAD model enables systematic quantification and validation of expressive robot behaviour. Prior work, such as Marmpena et al. (2018), demonstrates the model's suitability for capturing perceived emotional qualities in expressive body gestures, while Nunnari et al. (2023) show its effectiveness for characterizing continuous emotional responses in robot-avatar interactions.

Integrating the VAD model into the development pipeline ensures that the animation tools generate not only kinematically coherent movement but also trajectories with measurable affective structure. This approach strengthens the connection between expressive motion design and the production of quantifiably affective trajectories.

Methodology

This section describes the three software tools developed in this work to enhance expressivity in robot movements. Each tool is described in terms of its technical implementation as well as its functional relationship to the LMA and VAD frameworks for qualitative and affective control of expressive motion respectively.

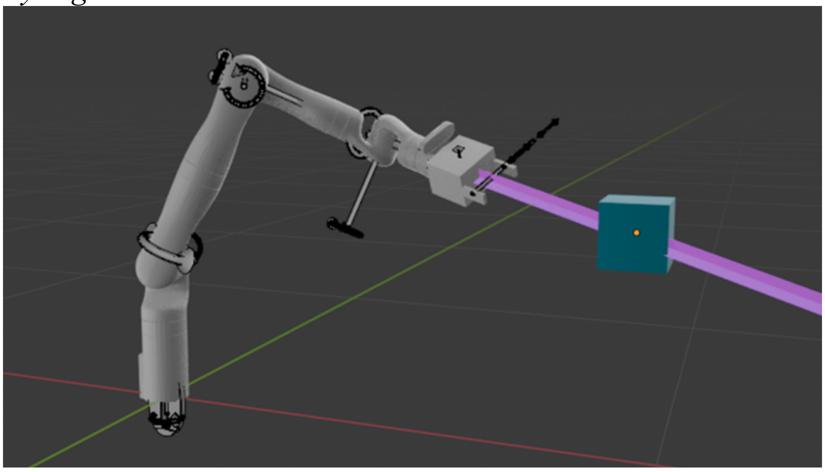
Eyesight Tool

Gaze constitutes a primary non-verbal communication modality that frequently precedes physical action and serves as an anticipatory cue in joint activity (Admoni & Scassellati, 2017). Within HRI, explicit modulation of gaze behavior has been shown to enhance coordination fluency and improve operators' ability to predict robot intentions, thereby aligning the collaborative dynamics in HRI more closely with human-human teams (Ronckers, 2022).

In response to these insights, the Eyesight Tool was designed to provide animators with fine-grained control over robot gaze behaviour within a unified 3D animation environment. The tool incorporates an adjustable visual proxy implemented as paired planar elements parented to the robot's end-effector that acts as a real-time indicator of the robot's inferred line of sight

(Figure 1). This tool enables animators to visualize and precisely calibrate the gaze direction, angular offsets, and target alignment without transitioning between software platforms. By moving congruently with the end-effector during trajectory design, the planes supply continuous spatial feedback, thereby supporting a more streamlined, agile, and precise animation workflow.

Figure 1
Eyesight Tool



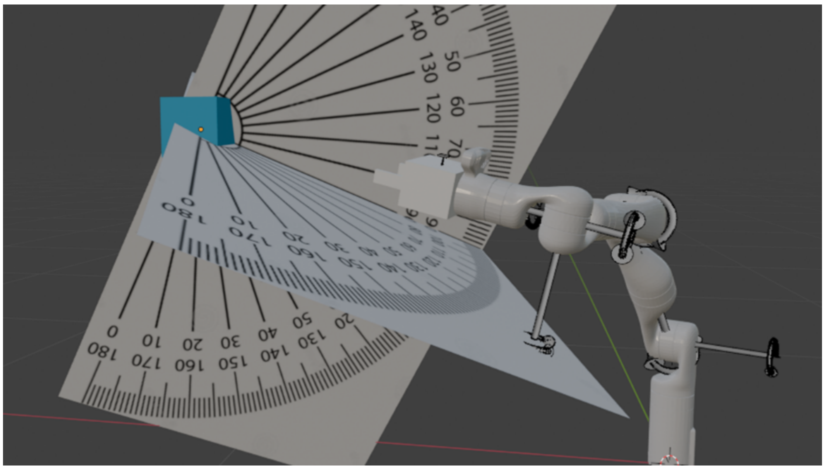
With respect to the LMA framework, the Eyesight tool directly operationalizes characteristics associated with the Effort-Space construct. In LMA, Space reflects the performer's attentional orientation toward the environment, varying between Direct (single-focused and goal-oriented) and Indirect (multi-focused, diffused, and flexible). Manipulating gaze offset allows animators to shape the perceived intentionality of motion: minimal offset generates a direct, decisive, and highly focused movement quality, whereas increased offset yields a more exploratory or hesitant character. These spatial qualities correlate with affective interpretations, where direct gaze is typically associated with approach-oriented emotions (e.g., joy, affection, or anger), and indirect or averted gaze corresponds to avoidance-oriented states such as embarrassment or uncertainty (Adams & Kleck, 2005).

Furthermore, with respect to the VAD framework, the Eyesight Tool primarily modulates the Dominance dimension, ranging from submissive to dominant. Recent studies indicate that sustained, direct gaze increases perceived dominance, whereas gaze aversion or wandering gaze trajectories reduce dominance and instead evoke submissiveness, uncertainty, or lowered agency (Shang et al., 2008). Thus, the Eyesight tool enables animators to encode dominance-related affective cues directly into robotic motion trajectories.

Protractor Tool

Building upon the role of gaze as a non-verbal communicative signal, the spatial orientation of a robot's end-effector toward a target object acts as an additional channel through which intent and affective state can be communicated. Prior findings demonstrate that variations in elevation (top-down) and azimuth (left-right) angles convey distinct emotional cues; for example, upward tilting is associated with positive affective states such as joy and excitement, whereas downward tilting frequently corresponds to negatively valenced emotions, including fear and sadness (Samanta & Guha, 2017; Sauter, 2017). To enable animators to systematically modulate this expressive parameter, the protractor tool was developed, which facilitates precise angular configuration of the robot's gaze towards the target object.

Figure 2
Protractor Tool



The tool incorporates two orthogonally oriented, protractor-projected planes that are parented to the target object (Figure 2). This configuration generates a stable visual reference frame for measuring and adjusting end-effector orientation. Animators can manipulate angular alignment through standard 3D interaction modalities (pan, tilt, and rotate) allowing the gaze angle to be tuned directly within the animation environment. As the tool is anchored to the target object, users can immediately assess the relational geometry between the manipulator and its intended point of focus, eliminating dependence on external visualization utilities, thereby improving workflow efficiency and precision during motion design.

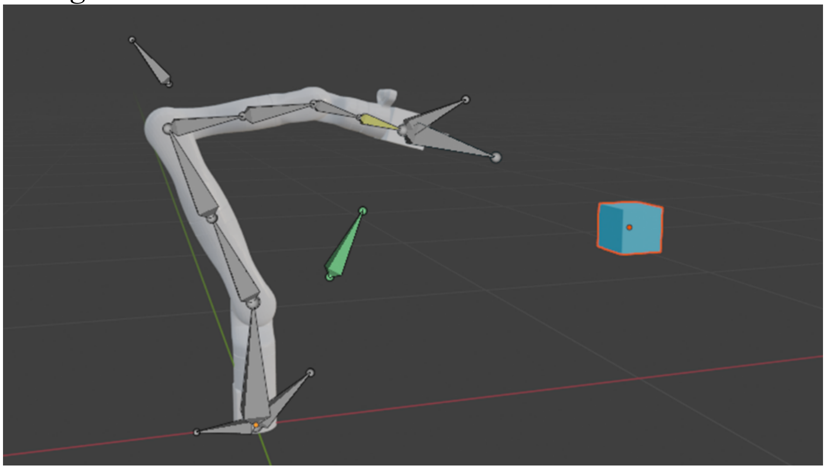
With respect to the LMA framework, the Protractor Tool primarily influences the Effort-Flow construct. Flow characterizes the degree of movement continuity, ranging from Bound, which is highly controlled, deliberate, and stabilized, to Free, which is more fluid, uninterrupted, and dynamic. When animators adopt a Bound-Flow strategy using precise, fixed angular specifications with minimal deviation, the resulting gaze appears intentional and constrained. Conversely, employing smoother, continuous angular variations yield a Free-Flow quality, producing movements perceived as relaxed and naturalistic.

Within the VAD model, the Protractor Tool provides control over emotional expressivity by encoding angular direction as a determinant of both Dominance and Valence. Empirical evidence indicates that downward-directed gaze from an elevated perspective signals dominance and assertiveness, whereas an upward-directed gaze suggests deference, submission, or admiration (Main et al., 2009; Robinson et al., 2008). Additionally, vertical head orientation modulates Valence: upward angles (raised head) correlate with positively valenced states such as joy or contentment, while downward inclinations (bowed head) correspond to negatively valenced emotions including sadness or fear (Sauer et al., 2013). Accordingly, the Protractor Tool enables systematic shaping of affective interpretation through precise orientation control.

IK Rig Tool

The third tool developed in this project is an Inverse Kinematics (IK) rig, informed by the foundational approaches of Starke et al. (2018) and Ribeiro and Paiva (2017), which demonstrated how IK frameworks can be extended beyond conventional character animation to support constrained robot motion generation incorporating realistic joint limits and safety requirements.

Figure 3
IK Rig Tool



In contrast to the FK/IK rig implemented on a custom-built robot in the work of Ribeiro and Paiva (2017), our workflow began by importing the Kinova cobot's URDF model into Blender using the Phobos plugin. As Phobos generates only an FK rig, offering fine-grained joint control but lacking intuitive end-effector manipulation, we developed a supplementary IK rig as a visualization and rapid posing tool to investigate whether IK-based movement visualization could enhance trajectory design efficiency for low-DoF collaborative manipulators.

This resulted in a dual-rig system: the IK rig enables rapid pose prototyping through intuitive end-effector manipulation, while the Phobos-generated FK rig serves as the authoritative model for validating joint feasibility and safety constraints. Poses created with the IK rig are subsequently replicated on the FK rig to ensure physical plausibility. For implementation, we adopted the orientation-constraint strategy from (Ribeiro & Paiva, 2017) to maintain compliance with Kinova's joint limits. Additionally, we integrated a Pole Target mechanism (Blender Documentation Team, 2025) to address IK chain instability described in Ribeiro and Paiva's work (2017) thereby improving directional control of the robot. Although this configuration is not designed to manage highly complex or over-constrained postures, it robustly supports essential tasks such as reaching, object-aligned positioning, and expressive redirection.

Within this system, the primary manipulated variables are the robot's whole-arm configuration and the end-effector's Cartesian position and orientation. These map onto LMA components of Effort and Shape, modulating qualities such as strength, control, expansion, and contraction. With respect to the VAD model, adjustments to posture, spatial openness, and movement speed and control influence all three emotional dimensions, enabling animators to craft motion trajectories with systematically encoded affective characteristics.

Experimental Design

IRB-approved human subjects' studies were conducted with 6 professional animators (Ages 21–30, Male = 3, F = 3) to assess the impact of the proposed animation tools on workflow efficiency and user experience. Three structured user studies were conducted, each tailored to the specific functionalities and constraints of an animation tool.

Hypothesis

In this work we test two hypotheses:

- H1: Eyesight, Protractor and IK rig animation tools improve animators' workflow efficiency.
- H2: Eyesight, Protractor and IK rig animation tools enhance the animators' design experience.

Measures

The evaluation of our proposed tools was conducted through a combination of quantitative and qualitative measures, detailed in the subsections below.

Objective Measures

Across the three user studies, quantitative evaluation of tool performance was conducted using the following dependent variables:

1. Animation Time for First Attempt – The time taken by the participant to create the initial animation that satisfies the minimum task requirements, recorded from task onset to first task-complete submission. This metric serves as a primary indicator of workflow efficiency and initial tool learnability.
2. Time Spent on Adjustments – The cumulative time required for refining the trajectory after the first attempt. This measure reflects the iterative effort needed to achieve precision. Reduced adjustment time suggests that a tool affords more accurate initial control or provides clearer feedback, thereby lowering the need for extensive revisions.
3. Number of Adjustments – The total number of attempts taken by the animator to refine the trajectory after the initial minimum-viability submission. Fewer attempts indicate higher tool precision, and alignment between animator intent and tool output.

Subjective Measures

Perceived usability and user experience can be assessed using the System Usability Scale (SUS), a standardized ten-item questionnaire comprising alternating positively and negatively phrased statements (Brooke, 1996). The phrasing was minimally adapted to fit the current context while preserving semantic integrity:

1. I think that I would like to use this tool frequently.
2. I found the tool unnecessarily complex.
3. I thought the tool was easy to use.
4. I think that I would need the support of a technical person to be able to use this tool.
5. I found the various functions in this tool were well integrated.
6. I thought there was too much inconsistency in this tool.
7. I would imagine that most people would learn to use this tool very quickly.
8. I found the tool very awkward to use.
9. I felt very confident using the tool.
10. I needed to learn a lot of things before I could get going with this tool.

Participants rated their agreement on a five-point Likert scale ("Strongly Disagree" to "Strongly Agree"), enabling evaluation of usability, learnability, and overall user satisfaction.

Protocol

The experimental protocol included pre-experiment training and grouping of participants, the main experiment with three user studies to evaluate each developed tool, and the post-experiment interview to acquire feedback from participants.

Pre-experiment Training

Upon providing informed consent, participants completed a preliminary survey documenting their years of experience in 3D animation and self-reported proficiency with Blender. To ensure a consistent baseline across all participants, an instructional video was then administered. This tutorial introduced both the default FK rig and the animation tools developed for the study, with emphasis on their functional differences, intended use cases, and operational controls.

Following the tutorial, participants engaged in a 10-minute guided practice session to familiarize themselves with the tools in a controlled environment. Participants were subsequently stratified into two groups, Group A (tool-assisted FK rig) and Group B (default FK rig), using a balanced assignment procedure based on reported experience and competency scores. This grouping strategy ensured equivalence in baseline skill levels, enabling a controlled assessment of how the developed tools influenced animation efficiency and user experience.

Main Experiment

The main experiment included three user studies where each study explored the specific functionalities and constraints of one animation tool. In each study participants had to design an expressive trajectory that not only accomplished a given task but was also kinematically safe to be deployed on robots. All submitted robot trajectories underwent a safety check using MATLAB. Four physical constraints specific to the Kinova single-arm robot were used for this assessment:

- Joint Angular Limit (Joint 2: ±128°, Joint 4: ±147°, Joint 6: ±120°),
- Joint Speed Limit (1.39 rad/s on Joints 1-4, 1.22 rad/s on Joints 5-7),
- Joint Acceleration Limit (5.2 rad/s² on Joints 1-4, 10.0 rad/s² on Joints 5-7),
- Joint Torque Limit (39.0 N·m on Joints 1-4, 9.0 N·m on Joints 5-7)

Animations violating any constraint were returned to participants for correction. This ensured that all trajectories remained within safe operational boundaries and were suitable for potential deployment on the Kinova platform.

- **Study 1 - Eyesight Tool**
  The first study assessed the usability and precision afforded by the Eyesight Tool. The robot arm was initialized in a standardized idle configuration oriented toward a 5-cm blue cubic target. Participants were instructed to animate a left-to-right “scanning” gaze motion, with the strict constraint that the end-effector should be oriented towards the cube (an imaginary line passing through the centre of the end effector should also pass through the cube) for the full duration of the animation. This task evaluated the tool’s effectiveness in supporting fine-grained control of gaze alignment and spatial precision.

- **Study 2 - Protractor Tool**
  The second study tested the Protractor Tool's capability in assisting precise angular control of the cobot's gaze direction. The experiment setup and robot initialisation mirrored Study 1. Participants were instructed to generate two discrete end-effector poses: Pose A (left-side approach) and Pose B (right-side approach), such that the cobot's gaze was directed at the cube from each side. The principal task requirement was angular symmetry with a tolerance of ±10° margin of error. This task evaluated the tool's ability to support consistent, bilateral angular positioning.

- **Study 3 - IK Rig Tool**
  The third study evaluated the IK rig through a 6D animation exercise where the animators had to control both, the position as well as the orientation of the end-effector. Group A utilised the developed IK rig along with the default FK rig, while Group B used only the default FK rig. All participants had to animate the robot's end-effector to reach the target cube by following a predefined frame's trajectory across space. This meant that the participants had to animate the end-effector such that it followed the positions as well as orientations of the moving frame to reach the target cube. This study assessed participants' ability to generate smooth, kinematically coherent trajectories and compared the efficiency of IK-assisted posing against direct FK articulation.

6.3.3 Post-Experiment Interview: Participants were asked open-ended qualitative questions to capture richer insights into their interpretation of the tool implementations. Participants were asked to compare the three tools, articulate their preferences, identify functional limitations, and propose enhancements to better align the tools with professional animation workflows.

Results and Discussion

This section presents the objective efficiency gains and the subjective usability ratings of each tool assessed through user studies.

Objective Evaluation

Six professional animators participated in the experimental studies. Quantitative analyses indicates different performance gains across the three animation tools, each contributing to workflow enhancements through distinct operational pathways.

Results corresponding to all tools support H1, confirming that tool integration measurably improves animation efficiency. The IK rig yielded the most substantial overall performance gains. Specifically, it reduced initial attempt duration from 632.33 seconds to 554.67 seconds, refinement time from 481.33 seconds to 339 seconds, and the number of attempts from 3.33 to 2.00. Furthermore, with the IK rig, refinement-time variability also diminished (Std. Dev. reduced from 95.23 to 58.42), suggesting that the IK system mitigated performance disparities among users with differing technical backgrounds. These findings demonstrate that, for fundamental alignment and posing tasks, an IK-based modelling layer is critical for stabilizing animator performance and supporting consistent spatiotemporal control.

On the other hand, the Protractor tool exhibited a different efficiency profile. While its impact on initial attempt time was negligible (607.67 seconds to 604 seconds), it produced pronounced reductions in refinement duration (474.33 seconds to 343 seconds) and number of attempts (4.00 to 3.33). Lower standard deviations across metrics confirm its role in promoting consistent animator decision-making. These results indicate that the Protractor tool primarily optimizes mid- to late-stage correction cycles by providing reliable angle-based feedback that reduces manual alignment adjustments.

By contrast, the Eyesight tool produced an increase in initial attempt time (665.33 s to 815 s), suggesting reduced efficiency. However, subsequent performance measures qualify this interpretation. Figure 6 shows that participants achieved perfect target alignment after a single additional attempt, eliminating the need for extended revision loops. Qualitative reports further clarify that animators deliberately invested additional time during the initial attempt to exploit the tool's precision-oriented affordances. Thus, despite initial slow-down, the tool reduced overall trial-and-error cycles and improved accuracy-driven workflows. Collectively, these findings demonstrate that while all tools reduce trial-and-error, each tool modulates animator behaviour differently: the IK rig accelerates the entire workflow, the Protractor tool compresses the refinement phase, and the Eyesight tool front-loads precision work to minimize downstream corrections.

Figure 4
Mean Time and Standard Deviations of First Attempt per Animation Tools; Tool-Assisted(W) vs. Without Tool (WO)

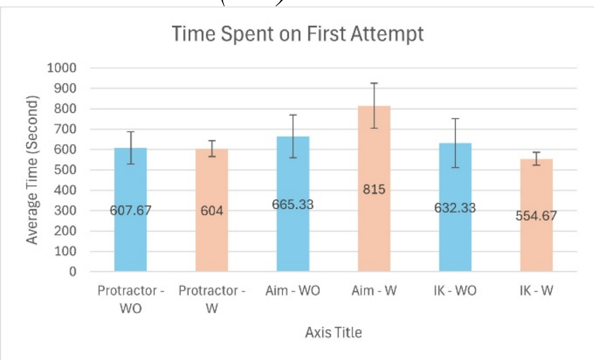


Figure 5
Comparison of Mean Refinement Time: Tool-Assisted(W) vs. Without Tool(WO)

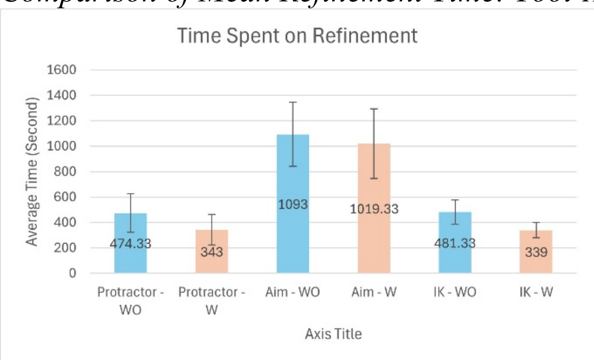
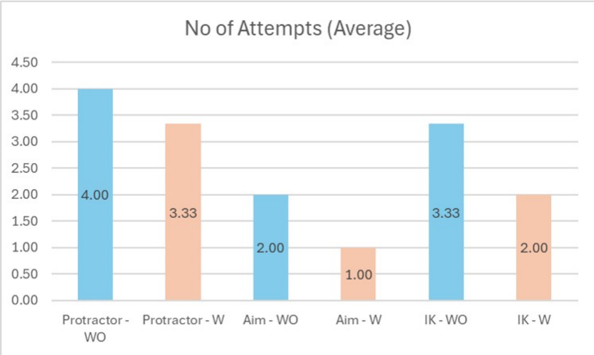


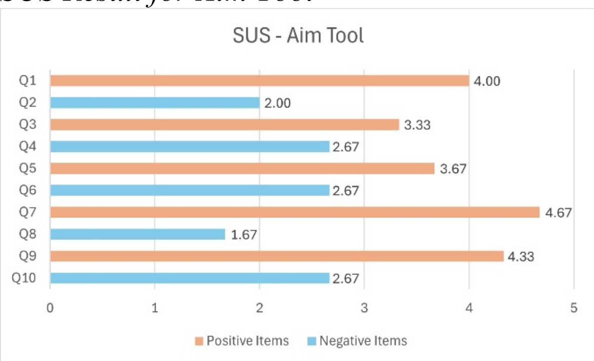
Figure 6
No of Attempts for Each Experiment; Tool-Assisted(W) vs. Without Tool (WO)



Subjective Evaluation

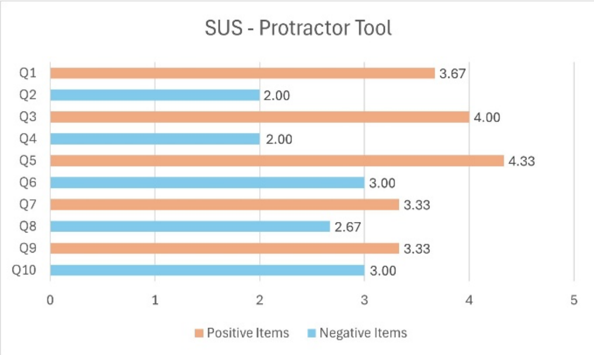
System Usability Scale (SUS) outcomes reveal clear stratification in perceived usability across the developed tools with only the Eyesight and Protractor tools supporting H2. The Eyesight tool achieved a score of 71.63 (Grade C, “Good”). As shown in Figure 7, all positive usability items received high average scores. The highest-rated aspects were the tool's ease of learning (Q7: 4.67), users' confidence in using it (Q9: 4.33), and their willingness to use it frequently (Q1: 4.00), highlighting its primary strength in learnability and straightforward operation. These results suggest that its dedicated functionality and predictable interaction pattern support rapid user adoption.

Figure 7
SUS Result for Aim Tool



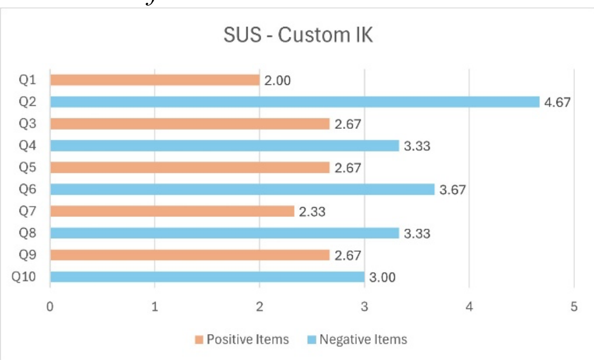
The Protractor tool similarly achieved a C-level usability score (66.67). Participants highlighted strong functional cohesion (Q5: 4.33), ease of use (Q3: 4.00), and intention to reuse the tool (Q1: 3.67). These ratings indicate that task-specific, lightweight tools are perceived as operationally coherent and intuitively aligned with existing animation practices.

Figure 8
SUS Result for Protractor Tool



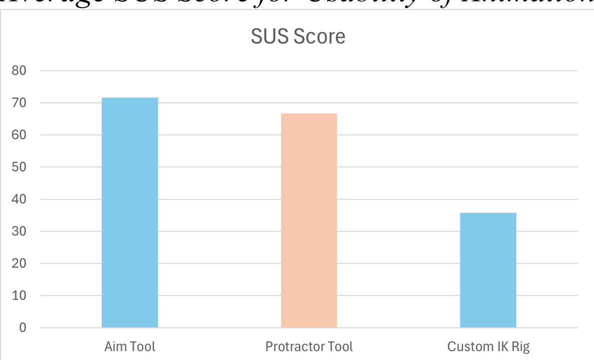
In contrast, the IK rig received a SUS score of 35.83 (Grade F, "Poor"). Negative-item responses were markedly elevated, particularly regarding perceived complexity (Q2: 4.67), inconsistency (Q6: 3.67), and dependency on external support (Q4 & Q8: 3.33). Although the IK rig objectively enhanced performance, participants reported that its current visualization and interaction design lacked usability, hindering its practical integration into their workflow.

Figure 9
SUS Result for Protractor Tool



User feedback further clarified the discrepancy between objective and subjective outcomes for the IK system. Although animators enjoyed using the Eyesight and Protractor tools, they expressed a preference for hybrid FK/IK rigs with seamless switching over the current dual-rig system. Seamless switching between FK and Ik is an industry-standard approach that better supports nuanced pose sculpting and adheres to familiar animation pipelines.

Figure 10
Average SUS Score for Usability of Animation Tools



Conclusion

This study presents a tool-centric methodology for robotic animation, comprising three software tools designed to improve animator control and alignment with robot's kinematic and operational constraints. Empirical evaluations demonstrate that the tools significantly enhance animation efficiency, particularly for tasks involving fine-grained expressive behaviours such as gaze alignment. These findings emphasize the utility of structured, tool-assisted workflows for animating low degree-of-freedom collaborative robots.

In the current evaluation, each tool was assessed independently with tool-specific tasks, limiting ecological validity. A more comprehensive assessment requires examining their performance within a fully integrated production workflow representative of real-world animation pipelines. Future work will focus on developing a unified FK/IK rig that enables intuitive IK-driven posing while automatically enforcing kinematic feasibility and safety compliance. In parallel, we aim to integrate all three tools into a cohesive animation environment to investigate their combined impact on animator performance.

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References

Adams, R. B., & Kleck, R. E. (2005). *Effects of direct and averted gaze on the perception of facially communicated emotion. Emotion*, *5*(1), 3–11. https://doi.org/10.1037/1528-3542.5.1.3

Admoni, H., & Scassellati, B. (2017). Social Eye Gaze in human-robot interaction: A Review. *Journal of Human-Robot Interaction*, *6*(1), 25. https://doi.org/10.5898/jhri.6.1.admoni

Bacula, A., & LaViers, A. (2020). Character synthesis of ballet archetypes on robots using Laban Movement Analysis: Comparison between a humanoid and an aerial robot platform with lay and expert observation. *International Journal of Social Robotics, 13*(5), 1047–1062. https://doi.org/10.1007/s12369-020-00695-0

Banh, A., Rea, D. J., Young, J. E., & Sharlin, E. (2015). Inspector baxter: The social aspects of integrating a robot as a quality inspector in an assembly line. *Proceedings of the 3rd international conference on human-agent interaction*, 19–26. https://doi.org/10.1145/2814940.2814955

Bartenieff, I., & Davis, M. (1965). Effort-shape Analysis of Movement: The Unity of Expression and Function. By Irmgard Bartenieff, Martha Ann Davis. *Albert Einstein College of Medicine, Yeshiva University.*

Bates, J. (1994). The role of emotion in believable agents. *Communications of the ACM*, *37*(7), 122–125. https://doi.org/10.1145/176789.176803

Beck, A., Stevens, B., Bard, K. A., & Cañamero, L. (2012). Emotional body language displayed by artificial agents. *ACM Transactions on Interactive Intelligent Systems, 2*(1), 1–29. https://doi.org/10.1145/2133366.2133368

Blender Documentation Team. (2025). *Inverse Kinematics Constraint - Blender 5.0 Manual.* (2025, December 16). Retrieved Nov 9, 2025, from https://docs.blender.org/manual/en/latest/animation/constraints/tracking/ik_solver.html

Breazeal, C., Kidd, C. D., Thomaz, A. L., Hoffman, G., & Berlin, M. (2005). Effects of nonverbal communication on efficiency and robustness in human-robot teamwork. In *2005 IEEE/RSJ international conference on intelligent robots and systems,* 708–713. https://doi.org/10.1109/iros.2005.1545011

Brooke, J. (1996). SUS: A “quick and dirty” usability scale. *Usability Evaluation In Industry*, 207–212. https://doi.org/10.1201/9781498710411-35

Burgoon, J. K., Guerrero, L. K., & Manusov, V. (2011). *Nonverbal signals. Handbook of interpersonal communication*, 239–280. SAGE Publications.

Cheng, S. (2017). Study of emotion rendering design for humanoid robots compiled with real-time music mood perception. *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN),* 647–652. https://doi.org/10.1109/roman.2017.8172371

Epic Games. (n.d.). *Unreal Engine* [Computer software]. Epic Games. https://www.unrealengine.com/

Fiore, S. M., Wiltshire, T. J., Lobato, E. J., Jentsch, F. G., Huang, W. H., & Axelrod, B. (2013). Toward understanding social cues and signals in human–robot interaction: Effects of robot gaze and proxemic behavior. *Frontiers in Psychology, 4*. https://doi.org/10.3389/fpsyg.2013.00859

Grushko, S., Vysocký, A., Oščádal, P., Vocetka, M., Novák, P., & Bobovský, Z. (2021). Improved mutual understanding for human-robot collaboration: Combining human-aware motion planning with haptic feedback devices for communicating planned trajectory. *Sensors*, *21*(11), 3673. https://doi.org/10.3390/s21113673

Hirano, T., Shiomi, M., Iio, T., Kimoto, M., Tanev, I., Shimohara, K., & Hagita, N. (2017). How do communication cues change impressions of Human–Robot Touch Interaction? *International Journal of Social Robotics*, *10*(1), 21–31. https://doi.org/10.1007/s12369-017-0425-8

Kinova Robotics. (2020). *Gen3 Ultra lightweight robot User Guide (Release 07).* Retrieved Nov 9, 2025, from https://www.kinovarobotics.com/uploads/User-Guide-Gen3-R07.pdf

Kompatsiari, K., Tikhanoff, V., Ciardo, F., Metta, G., & Wykowska, A. (2019). The importance of mutual gaze in human-robot interaction. *International conference on social robotics*, 443–452. https://doi.org/10.31234/osf.io/2ndzf

Lasseter, J. (1987). Principles of traditional animation applied to 3D computer animation. *ACM SIGGRAPH Computer Graphics*, *21*(4), 35–44. https://doi.org/10.1145/37402.37407

Lichtenthäler, C., & Kirsch, A. (2013). Towards legible robot navigation-how to increase the intend expressiveness of robot navigation behavior. In *International Conference on Social Robotics-Workshop Embodied Communication of Goals and Intentions.* https://hal.science/hal-01684307/

Main, J. C., Jones, B. C., DeBruine, L. M., & Little, A. C. (2009). Integrating gaze direction and sexual dimorphism of face shape when perceiving the dominance of others. *Perception*, *38*(9), 1275–1283. https://doi.org/10.1068/p6347

Marmpena, M., Lim, A., & Dahl, T. S. (2018). How does the robot feel? perception of valence and arousal in emotional body language. *Paladyn, Journal of Behavioral Robotics*, *9*(1), 168–182. https://doi.org/10.1515/pjbr-2018-0012

Masuda, M., & Kato, S. (2010). Motion rendering system for emotion expression of human form robots based on Laban Movement Analysis. *19th International Symposium in Robot and Human Interactive Communication*, 324–329. https://doi.org/10.1109/roman.2010.5598692

Nunnari, F., Nicora, M. L., Prajod, P., Beyrodt, S., Chehayeb, L., Andre, E., Gebhard, P., Malosio, M., & Tsovaltzi, D. (2023). Understanding and mapping pleasure, arousal and dominance social signals to robot-avatar behavior. *2023 11th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW)*, 1–8. https://doi.org/10.1109/aciiw59127.2023.10388078

Raghu, S. B., Lohrmann, C., Bakshi, A., Kim, J., Herrera, J. C., Hayes, B., & Roncone, A. (2025). Employing laban shape for generating emotionally and functionally expressive trajectories in robotic manipulators. *2025 34th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN),* 1201–1208. https://doi.org/10.1109/ro-man63969.2025.11217717

Reilly, W. S. (1996). Believable Social and Emotional Agents. *Ph.D. Dissertation, Carnegie Mellon University*. https://apps.dtic.mil/sti/html/tr/ADA310766/

Ribeiro, T., & Paiva, A. (2012). The illusion of Robotic Life. *Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction*, 383–390. https://doi.org/10.1145/2157689.2157814

Ribeiro, T., & Paiva, A. (2014). Make Way for the Robot Animators!. *Artificial Intelligence for Human-Robot Interaction: Papers from the 2014 AAAI Fall Symposium*, 131–133. https://cdn.aaai.org/ocs/9097/9097-40082-1-PB.pdf

Ribeiro, T., & Paiva, A. (2017). Animating the Adelino Robot with Erik: The expressive robotics inverse kinematics. *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, 388–396. https://doi.org/10.1145/3136755.3136791

Ribeiro, T., Paiva, A., & Dooley, D. (2013). Nutty tracks. *ACM SIGGRAPH 2013 Posters,* 1–1. https://doi.org/10.1145/2503385.2503394

Robin, K. (2011). A brief overview of Laban Movement Analysis. *CLMA*. https://psychomotorischetherapie.info/website/wp-content/uploads/2015/10/LMA-Workshop-Sheet-Laban.pdf

Robinson, M. D., Zabelina, D. L., Ode, S., & Moeller, S. K. (2008). The vertical nature of dominance-submission: Individual differences in vertical attention. *Journal of Research in Personality*, *42*(4), 933–948. https://doi.org/10.1016/j.jrp.2007.12.002

Ronckers, M. L. (2022). Animal-like Referential Gaze in a Robot Arm improves Human-Robot Collaboration: Going Beyond Humanoid Design.

Saldien, J., Vanderborght, B., Goris, K., Van Damme, M., & Lefeber, D. (2014). A motion system for social and animated robots. *International Journal of Advanced Robotic Systems*, *72*. https://doi.org/10.5772/58402

Samadani, A.-A., Burton, S., Gorbet, R., & Kulic, D. (2013). Laban effort and shape analysis of affective hand and arm movements. *2013 Humaine Association Conference on Affective Computing and Intelligent Interaction*, 343–348. https://doi.org/10.1109/acii.2013.63

Samanta, A., & Guha, T. (2017). On the role of head motion in Affective Expression. *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* 2886–2890. https://doi.org/10.1109/icassp.2017.7952684

Sauer, A., Mothes-Lasch, M., Miltner, W. H., & Straube, T. (2013). Effects of gaze direction, head orientation and valence of facial expression on amygdala activity. *Social Cognitive and Affective Neuroscience*, *9*(8), 1246–1252. https://doi.org/10.1093/scan/nst100

Sauter, D. A. (2017). The nonverbal communication of positive emotions: An emotion family approach. *Emotion Review*, *9*(3), 222–234. https://doi.org/10.1177/1754073916667236

Schulz, T., Holthaus, P., Amirabdollahian, F., Koay, K. L., Torresen, J., & Herstad, J. (2019). Differences of human perceptions of a robot moving using linear or slow in, slow out velocity profiles when performing a cleaning task. *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN),* 1–8. https://doi.org/10.1109/ro-man46459.2019.8956355

Shang, J., Liu, Y., & Fu, X. (2008). Dominance modulates the effects of eye gaze on the perception of threatening facial expressions. *2008 8th IEEE International Conference on Automatic Face & Gesture Recognition*, 1–6. https://doi.org/10.1109/afgr.2008.4813469

SideFX. (n.d.). *HOUDINI* [Computer Software]. SideFX. https://www.sidefx.com/

Starke, S., Hendrich, N., & Zhang, J. (2018). Memetic evolution for generic full-body inverse kinematics in robotics and animation. *IEEE Transactions on Evolutionary Computation*, *23*(3), 406–420. https://doi.org/10.1109/tevc.2018.2867601

Szafir, D., Mutlu, B., & Fong, T. (2015). Communicating directionality in flying robots. *Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction*, 19–26. https://doi.org/10.1145/2696454.2696475

Tabrez, A., Luebbers, M. B., & Hayes, B. (2020). A survey of mental modeling techniques in human–robot teaming. *Current Robotics Reports*, *1*(4), 259–267. https://doi.org/10.1007/s43154-020-00019-0

Takayama, L., Dooley, D., & Ju, W. (2011). Expressing thought: improving robot readability with animation principles. *Proceedings of the 6th international conference on Human-robot interaction*, 69–76. https://doi.org/10.1145/1957656.1957674

Terzioğlu, Y., Mutlu, B., & Şahin, E. (2020). Designing social cues for collaborative robots: the role of gaze and breathing in human-robot collaboration. *Proceedings of the 2020 ACM/IEEE International Conference on Human-Robot Interaction*, 343–357. https://doi.org/10.1145/3319502.3374829

Thiebaux, M., Marsella, S., Marshall, A. N., & Kallmann, M. (2008). Smartbody: Behavior realization for embodied conversational agents. *Proceedings of the 7th international joint conference on Autonomous agents and multiagent systems-Volume 1*, 151–158.

Thomas, F., & Johnston, O. (1995). *The illusion of life: Disney animation.* Hyperion, U.S.

van Breemen, A. J. N. (2004). Animation engine for believable interactive user-interface robots. *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*, *3*, 2873–2878. https://doi.org/10.1109/iros.2004.1389845

Verma, G. K., & Tiwary, U. S. (2016). Affect representation and recognition in 3D continuous valence–arousal–dominance space. *Multimedia Tools and Applications, 76*(2), 2159–2183. https://doi.org/10.1007/s11042-015-3119-y

Walker, M., Hedayati, H., Lee, J., & Szafir, D. (2018, February). Communicating robot motion intent with augmented reality. *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction*, 316–324. https://doi.org/10.1145/3171221.3171253